The Impact of Blockchain Related Name Changes on Corporate Performance

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Abstract

This paper examines the impact of blockchain and crypto-related name changes on corporate and financial performance of the corporations. We document several pieces of evidence suggesting that companies who partake in such "crypto-exuberant" naming practices become more volatile and offer substantial and persistent stock market premiums as a reward for their corporate identity change. However, the retroactive name changes harm firm's short-term profitability and have a dampening effect on financial leverage of the company. This paper advances the Dotcom effect literature by providing novel results on the changing traditional pathways of price discovery and information flows after the announcement of corporate name changes to blockchain-related names. The identified contagion channels display that crypto-exuberant companies become more susceptible to cryptocurrency markets, which should interest regulators and investors.

Keywords: Blockchain; Cryptocurrency; Crypto-Exuberance; Dotcom Effect; Information Asymmetry; Corporate Name Changes.

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1. Introduction

Following a period of rapid FinTech adoption, and evidence of increasing popularity of this new technology among investors, many companies have announced the incorporation of blockhain and cryptocurrency-related terms to be included in their corporate name and branding. In this paper, we demonstrate that name-changing announcements generated diverse effects on the financial performance of the corporations which go beyond the 'investor mania' (Cooper et al. [2001]) and 'Dot.com' effects reported in previous literature (Bosch and Hirschey [1989]; Karpoff and Rankine [1994]). There are several genuine reasons as to why investors and companies would be interested in blockchain and cryptocurrencies. The main problem, however, is that companies often have little or no intention to adopt cryptocurrency but are trying to take advantage of the popularity of this technology among investors.

A notable example is Eastman Kodak's announcement to enter the cryptocurrency market in January 2018. This announcement caused a sharp appreciation in Kodak's share price from \$3.10 to \$12.75 in less than 24 hours after the announcement. According to Corbet et al. [2020], this sharp increase in equity returns after the cryptocurrency announcement was not necessarily related to a revolutionary nature or superior characteristics of the proposed KodakCoin platform. This example postulated the emergence of a new type of information asymmetry that can cause a spillover effect from cryptocurrency markets to equity markets. After the announcement, Kodak returns became increasingly correlated with bitcoin, providing supportive evidence that equity returns absorbed some of the bubble-like characteristics of cryptocurrencies that have been unveiled by Cheah and Fry [2015], Corbet et al. [2018], among others.

This paper utilises a sample of 82 companies that changed their names in the period from 30 December 2015 to 25 June 2019. Specifically, we contrast the effect of name changes in two groups of companies: (i) companies that change their names to incorporate blockhain or cryptocurrency-related naming; and (ii) companies that changed their names without any cryptocurrency or blockhain associations. The analysis proceeds in three stages. At the first stage of our analysis, we perform a panel regression model to test whether retroactive announcements affect the profitability and financial leverage of the firms. At the second stage, we test the investment mania hypothesis in a similar manner to Cooper et al. [2001] using a combination of traditional time-series models. As a robustness test, we consider the bitcoin-bubble period to analyse abnormal returns during the peak of bitcoin popularity. At the third stage, we analyse the channels of the information flows and price discovery following cryptocurrency-related announcements. The results display the substantial internal differentials between companies who utilise corporate crypto-exuberant name changes when compared to a group of non-blockchain or crypto-related corporate re-branding.

The paper contributes to the previous literature in two main ways. First, this paper contributes to the growing body of FinTech literature. Over the last decades, FinTech literature expanded significantly, shedding the light on a variety of risk-return characteristics of crypto-assets, such as cryptocurrency market bubble, volatility, liquidity, contagion effects and diversification benefits (e.g. Corbet et al. [2018], Fry [2018], Felix and von Eije [2019]), as well as issues associated with cybercriminality (Foley et al. [2019]) and data quality (Alexander and Dakos [2020]). However, there is only limited evidence on stock price reactions to the corporate name changes driven by the intention to incorporate blockchain and cryptocurrency association. In most cases examined, we identified that no structural change has taken place apart from a change of corporate brand and image. Furthermore, no indications of any blockchain or cryptocurrency investment have been provided by those companies except their intention to do so. Akyildirim et al. [2020] analysed the potential misuse of the corporate blockhain announcements and called this effect '*crypto-exuberance*'.

While secondly, this paper contributes to the literature on corporate name changes and corporate re-identification (Karpoff and Rankine [1994], Cooper et al. [2001], Wu [2010]), as well as information asymmetry debates (Alford and Jones [1998], Boulton and Campbell [2016], Bajo and Raimondo [2017], Chen [2019]). Our results show that the effect of the crypto-related name changes alone produced substantial cumulative abnormal returns after the announcement day. We show that crypto-exuberance can be compared to the Dotcom bubble effect reported in early studies (Cooper et al. [2001]), however, this is a new phenomenon and effects are broader. Specifically, we identify the contagion effect from cryptocurrency markets to the crypto-exuberant group of companies. Such direct financial impacts are particularly surprising, as in the majority of companies identified, there have been no structural changes in the company at the time of the announcement with the exception of the change in corporate identity. Our results show that crypto-exuberance is a new form of information asymmetry, beyond the investment mania documented by previous studies.

This paper reports several novel findings which are interesting for investors and financial regulators alike. With respect to business operations perspective, we find that crypto-related name changes directly harm the short-term profitability of the companies. Furthermore, these companies are also found to decrease their financial leverage in the following quarter after the announcement, which is not evident for non-blockchain nor non-crypto-related group. With regard to pricing dynamics, we find substantial evidence of high crypto-exuberant pricing premiums, acting as a reward for companies that utilise such questionable tactics.

For investors, our results offer evidence that the premiums are also found to persist for up to six months after the announcement. This demonstrates significantly stronger persistence in comparison to the Dotcom effect. However, due to the sharp increases in the volatility and higher extreme returns of share price performance, investors should be aware that crypto-exuberant companies become much riskier investment after the name change. These results can be explained by the fact that those companies are self-selecting when incorporating high-risk blockchain and cryptocurrency technology as a central theme of their perceived business image.

For financial regulators, our findings offer a novel insight on cross-asset relationships. We report that crypto-exuberant companies are found to have a decrease in dynamic correlations with the domestic exchange on which they trade, while simultaneously an increase in dynamic correlations with cryptocurrency markets. This result verifies the changing investor perceptions of such a decision to change corporate identity in this manner. This finding is also important for portfolio managers, who wish to increase portfolio returns attracted by blockhain and crypto-related name change announcements. It is important to note that only the key decision-makers within the company know for certain as to whether the new corporate association with blockchain and cryptocurrency will ever develop to generate technological developments. The use of such crypto-exuberant behaviour appears to have generated substantial information asymmetry and has shrouded the transparency of such corporations, necessitating immediate investigations into the true rationale behind the decisions to utilise such behaviours.

The rest of this paper is as follows. In Section 2, we briefly review the relevant information asymmetry and corporate identity literature to develop testable hypotheses. Section 3 presents a concise overview of the data used in this research, while Section 4 discusses the methodologies employed. Section 5 presents a concise overview of the results presented, while Section 6 concludes.

2. Literature review and hypotheses development

There are several ways that a name change of a company might have an impact on that company's financial variables, both on the book and in the market. Indeed, Green and Jame [2013] show that even the fluency of the company name has positive impact on both market and book variables (see also Corbet et al. [2020]).[1] Prior literature suggests that corporate name change is a common tool in company re-identification, and more than 30% of US listed firms changed their name at least once, mainly driven by desire to disassociate from a brand with a poor reputation to a brand with a good reputation (Wu [2010]). Specifically, companies with unfavourable media coverage, poor accounting and past stock performance, tend

[1] Apart from these studies in the naming literature, Fryer and Levitt [2004] even revealed that naming black people distinctively led to the rise of the Black Power movement and is also a strong signal of socioeconomic status.

to go for more radical name changes, however, Wu [2010] reports that these radical changes fail to positively affect the stock price after the announcements. Kashmiri and Mahajan [2015] further distinguish between stock market response to proactive and retroactive name changes. It was found that companies that change their names to effectively communicate a real change in their scope of business tend to benefit more than companies that change their names to retroactively align their names with a new scope.

Crypto-exuberance can be compared to the Dotcom bubble effect reported in early studies, and we build our research particularly on those papers that analysed companies who added ".com" to the names and experienced substantial growth in share price after the announcement. Cooper et al. [2001] analysed the stock market reaction to the announcement of name changes to Internet-related dot-com names, and found that over the 5- and 11-days period after the name changes, the dotcom firms earn significant excess returns of 64% and 72%, respectively, in comparison to the non-Internet name-changing group. This paper provides alternative findings to earlier studies by Bosch and Hirschey [1989] and Karpoff and Rankine [1994] that found insignificant premiums following the name-changes announcement date. Naturally, important questions arise: Why do findings by Cooper et al. [2001] contradict to earlier studies? and, is the Dotcom effect truly a unique phenomenon, or can we observe similar patterns using more recent blockchain and FinTech innovations?

For companies, a blockchain and distributed ledger technology offer opportunity to decentralised information storage and transfer information between various parties without any third party authorisation. This provides numerous possibilities such as the creation of decentralised businesses, capital raising without any help of intermediaries and payment agents, generating a built-in customer base and positive network effects (Adhami et al. [2018], Giudici and Rossi-Lamastra [2018]). For investors, cryptocurrencies tend to be appealing due to their anonymity, lack of third-party interventions, tax advantages, low transaction costs, and convenience of mobile payments (Corbet et al. [2019]).

In particular, a name change related to blockchain or cryptocurrency might create the signal that the company is now aiming to make business in these areas. Since these business areas are perceived as highly speculative by many market participants, the name change can create a negative popularity, therefore might lead to decreased business activity and harder access to borrowing, which would be reflected as decreased profitability and leverage on the financial statements of the company. Thus, we specify the following hypotheses:

- H_1: *Crypto-related name changes harm companies' next term profitability, however this is not the case for non-crypto related name changes.*
- H_2: *Companies with crypto-related name changes (have to) decrease their financial leverages in the following financial term, however this is not the case for the companies with non-crypto related name changes.*

Moreover, due to the highly speculative cryptocurrency hype, company's share price might experience dramatic increases in the short term. In FinTech literature, Felix and von Eije [2019] investigated Initial Coin Offerings (ICOs) and found that there exists an average level of under-pricing of 123% for USA ICOs and 97% for the other countries examined. Chen [2019] linked the performance of ICO and the signalling theory by performing an empirical investigation of 626 ICO projects conducted from September 2015 to January 2018. The analysis of the impact of multi-channel signals during all ICO stages from the crowd sale to the coin listing revealed that information released via different disclosure channels may be interpreted by the investors in different ways, where social media platforms play vital role in information dissemination. Company stocks might seem to become more speculative in the eyes of the shareholders due to its involvement in such speculative business. Even though companies might have little or no intention to incorporate blockchain technology, due to the information asymmetry investors react to the announcements of crypto- or blockchain-related name change, regardless of the company's actual association with the distributed ledger technology.

In a similar context, Cooper et al. [2001] analysed the stock market reaction to the announcement of name changes to internet-related dot-com names and found evidence of abnormal returns on corporate stock within 10 working days after the announcement. The analysis of the sample containing 95 firms that announced name change in 1998-1999 revealed that association with Internet during this period allowed companies to significantly increase their value, which is evident across all firms, regardless of the company's actual involvement with the Internet. A similar study on the same subject was also performed by Lee [2001], providing close results to Cooper et al. [2001]. Motivated by the dotcom effect, we extend the earlier works by Jain and Jain [2019] and Sharma et al. [2020], and test the investment mania hypothesis, assuming that investors are eager to be associated with the blockchain and cryptocurrency at all costs:

- H_3: *Crypto-related name changes generate higher cumulative abnormal returns than non-crypto related name changes.*

Furthermore, we hypothesise that crypto-exuberant premiums will be more persistent in comparison to those observed in regular name change group, and we estimate the persistence of this phenomena in various event windows, from one day after the announcement to up to our maximum window of 180 days after the announcement. Particularly, we are interested to test the following hypothesis:

- H_4: *Crypto-exuberant name changing premiums tend to be more persistent than those for non-crypto-exuberant name change cases.*

There is a strong reason to believe that crypto-exuberant premiums might be substantially higher than the regular one. For regular name changes, previous literature suggests short-term and low premiums after the name changes. While Kot [2011] investigated the impact of corporate name changes on long-run performance of the stocks using a sample Hong Kong listed companies for the period from 1999 to 2008, only short-term effect has been identified, and it appeared that corporate name change has no impact on long-term operating performance of the firm. These results are in line with Bosch and Hirschey [1989] and Karpoff and Rankine [1994]'s findings that a stock price reaction to the name change announcement is very weak and is sensitive to sample selection.

While mainstream finance literature considered corporate re-branding and its impact on firm performance by utilising data sets containing companies that operate within established regulatory frameworks, we are examining the cases where companies are making decision to associate themselves with the business area where regulation framework is not yet clear. It is widely accepted that there are substantial ethical issues surrounding the use of cryptocurrency. One must widely consider as to why exactly a user of digital currency would explicitly want to mask their identity and develop a break in traceability. Regulatory bodies and policy-makers alike have observed the growth of cryptocurrencies with a certain amount of scepticism, based on this growing potential for illegality and malpractice. In fact, Foley et al. [2019] estimate that around $76 billion of illegal activity per year involve bitcoin (46% of bitcoin transactions). This is estimated to be in the same region of the U.S. and European markets for illegal drugs, and is identified as 'black e-commerce'.

While thorough investigation of the issues surrounding cryptocurrencies continues to develop, we continue to set out to analyse the potential mechanisms through which these new products can influence unsuspecting populations. Taking into account regulatory issues, information asymmetry and a lack of transparency present in FinTech area, we can expect that the effect of announcements will be even more pronounced for the crypto-related name changing announcements rather than for the regular names changes due to the uncertainties involved. Furthermore, due to the increased importance of social media (Chen [2019]) and speed of gathering information online, we expect to find more substantial and persistent premiums for crypto-related name changes than those reported for dotcom name changes by previous literature in early 2000s.

In addition to our earlier arguments, a comparison of explosive behaviour of cryptocurrency markets with Dotcom bubble is particularly important in the context of corporate name changes. In a recent study, Corbet et al. [2018] analyse the bitcoin bubble period using Phillips et al. [2015] methodology, and found that since bitcoin broke through the $1000 barrier in early 2017, there have been distinct periods denoted as bubbles. Furthermore, Corbet et al. [2018] identify several differences in the behaviour of bitcoin price returns in the pre- and post-$1000 sub-periods and evidence of asymmetric reverting patterns in the bitcoin price returns. Indeed, Cheng et al. [2019] argue that investors overreact to a firm's first 8-K disclosure of a potential foray into blockchain technology and that overreaction is a function of the bitcoin price bubble. This suggests that for accuracy of our analysis, we need to take into account potential difference in the results in pre-, during, and post-bubble periods:

- H_5: *Crypto-exuberant name premiums are higher for companies that announced the name change during the bitcoin pricing bubble period, and lower before and after bubble period, however, this is not the case for non-crypto-related name changes.*[2]

Loughran and Ritter [2004] examined the success of Initial Public Offering (IPOs) during the dotcom bubble, and found that first-day returns during the period of 1999-2000 reached 65.0%, which is significantly higher than full-sample average 18.7% during 1980-2003. Alford and Jones [1998] argued that information asymmetry increases as the amount or quality of public information decreases, thus an increase in the adverse selection component of the quoted bid-ask spread indicates the increase in information asymmetry. Their results display a lack of evidence that the low SEC regulation and disclosure requirement for foreign securities lead to higher information asymmetry for the foreign companies than for the US companies. Therefore, apart from bubble periods, it is important to control on geographic location of the companies, to identify in which countries the crypto-exuberant behaviour can offer the highest and most persistent premiums. In comparison to IPO where companies are

[2] Bitcoin is the cryptocurrency with largest market capitalisation, therefore for the purposes of this study it would be su□cient to use Bitcoin prices to test Hypothesis 5. Furthermore, Bitcoin has now developed in so far that it possesses a robust and liquid derivatives market when compared to a number of other traditional financial products (Corbet et al. [2018]).

obliged to disclose the information to investors and public by financial regulators, ICO is an alternative mechanism of raising funds by selling blockchain based tokens, and to date there is a lack of particular regulatory framework and disclosures requirements for ICO. Even though IPO and ICO share some similar characteristics, absence of regulation together with high volatility of cryptocurrency markets can cause higher information asymmetry during the ICO and during the announcements of name changes toward blockhain in general.

For the cases considered in this paper, however, the companies made announcements to enter blockchain and cryptocurrency market, yet, there were no further actions identified after the announcements have been made apart from the name change itself. Thus, the only driving force of the share price after the announcement might be the cryptocurrency and blockchain related hype, that is expected to be especially pronounced during the bitcoin bubble period. Furthermore, we hypothesise that higher and more persistent naming premiums might occur due to the the contagion effect from the speculative cryptocurrency markets to the shares of crypto-exuberant companies. Thus a thorough analysis of volatility before and after the announcements is required:

- H_6: *Crypto-exuberant name changing announcements make share price more susceptible to cryptocurrency market volatility, however this is not the case for non-crypto related name changes.*

Considering recent literature on cryptocurrency pricing dynamics, market efficiency and broad inherent risks, much research report the exceptional pricing volatility identified within cryptocurrency markets. Chaim and Laurini [2018] found that cryptocurrencies have very high unconditional volatility, and are subject to sudden, massive, price swings. Yi et al. [2018] found that the market for cryptocurrencies was tightly interconnected using a sample of 52 cryptocurrencies that were likely to propagate volatility shocks to others. According to Corbet et al. [2018], the cryptocurrency markets are relatively isolated from the financial and economic assets, but contain its own idiosyncratic risks that are difficult to hedge against.

However, as our understanding of FinTech evolves (Goldstein et al. [2019]) and the value of blockchain increases (Chen et al. [2019]), more research provide the evidence on the interactions across cryptocurrencies and between cryptocurrencies and traditional financial markets (Okorie and Lin [2020]). Therefore, it is of the utmost importance to protect broader markets from any exposure to contagion effects contained within these new financial products, especially until we develop a thorough understanding of the interactions contained within. Thus, we expect that when companies change their identity towards distributed ledger technology, their stocks will become susceptible to volatility shocks transmitting from the cryptocurrency markets. Furthermore, the higher cumulative abnormal returns might be observed for longer period of time due to the changes in channels of price discoveries and information flow. Hence, we analyse the change in information flow and price discovery, that should help us further to explain the behaviour of the companies stock after name changes in better details. Accordingly, share price might become more volatile and tend to move in more harmony with the cryptocurrencies while experiencing a decoupling effect from its peers in the stock market. All these arguments will be analysed thoroughly in the rest of the paper.

3. Data

We begin our analysis through the development of a concise list of announcements based on the intention to change the corporate identity of the company through changing name. Then we establish which of those companies partake in the 'crypto-exuberant' behaviour through the use of terms such as 'blockhain' or 'cryptocurrency' in their names. To develop such a dataset, 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 January 1, 2014 and July 16, 2019. The reason is that the name changes in our sample occur between December 30th, 2015 and June 25th, 2019. Therefore, the selected stock price period allows us to perform a pre- and post-name change analysis. We also note that there are no identified 'crypto-exuberant' announcements in the period prior to 2015.

There are two specific methodological approaches developed within our research. First, we specifically investigate as to whether there exist direct effects within the company as measured by internal financial performance across a number of theoretically supported, robust methodologies, while also considering the manner in which insiders' holdings or shares changed in the periods analysed. Second, we focus on the financial performance and investor perceptions of the name changes via a thorough analysis of share price volatility, the contagion of such volatility throughout related sectors, and the transfer of price discovery to specifically present evidence of changing investor behaviour. Our selected corporate account data is taken from Bloomberg. Stock price data is taken from Thomson Reuters Eikon.

The news selection rule is based on the source of the data. We develop on a combined search of LexisNexis, Bloomberg, and Thomson Reuters Eikon, eliminating web news and non-reputable online news sources, while searching for the keywords[3] under traditional corporate announcements. We do not consider the re-branding of sub-structure and internal corporate entities to be part of this sample. 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. 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. To omit

[3] The selected keywords used in this search include that of: "name change", "corporate identity", "cryptocurrency", "digital currency", "blockchain", "distributed ledger", "cryptography", "cryptographic ledger", "digital ledger", "altcoin" and "cryptocurrency exchange". In the respective search for traditional corporate name changes we search for terms such as "name change", "will change company name", "corporate rebranding", "corporate identity" amongst other similar variants for robustness. We do not consider changes of logo or companies with initials used for corporate identity that have, for example, changed one letter of their name.

issues with regards to stock illiquidity which presents substantial issue with regards to our selected methodology, we eliminated all companies that possessed at least three-separately identified consecutive two-hour periods with zero trading volumes at time periods with no stated stock market issues, such as induced closures for limit-up or limit-down for example, or indeed, technological fault. Such a rule eliminated companies that presented many significant periods of illiquidity and poor trading quality which would distort the analysis on their market variables.

We further supported the robustness of our final sample to eliminate exceptionally small companies through the inclusion of a rule that any company that is part of the final sample must have possessed a market capitalisation of above $50 million (USD), as calculated by the dollar-converted market capitalisation during the period of analysis. We repeat the implementation of these rules using multiple information providers and find that our final sample is robust regardless of source. Further, we considered the potential that other market moving events could have occurred during the same time period of analysis. To mitigate such effects, we search all news events during the time period surrounding each name change event using both Bloomberg and Eikon for robustness. A table of potential events that were considered to be influential are presented in the online Appendix, however, after consideration, results based on the key dates of crypto-exuberant name changes do not change significantly. To add further robustness, we further consider the use of the RepRisk database[4], and find that no reputationally damaging event is identified during any of the investigative windows denoted.

All observations found to be made on either a Saturday or Sunday (three announcements in total) are denoted as active on the following Monday morning. The dataset incorporates 82 total announcements made across 13 countries during the selected time period (incorporating Belgium, Canada, Germany, Hong Kong, Ireland, Israel, Norway, Poland, South Africa, South Korea, Taiwan, United Kingdom and the United States). All times are adjusted to

[4] The RepRisk Index (RRI) is a proprietary risk metric that quantifies a company's exposure to ESG and business conduct risks.

GMT, with the official end of day closing price treated as the listed observation for each comparable company when analysing associated contagion effects.

Insert Table 1 about here

The selected companies are presented in Table 1, where 31 companies are identified to have partaken in 'crypto-exuberant' naming behaviour, some of which were not ever before identified with any technological practice or development prior to the identified date. Further 51 companies are identified to have changed their name during the same analysed period which did not incorporate any cryptocurrency or blockchain naming characteristics. It is also of interest to consider the time-distribution of such 'crypto-exuberant' behaviour. In 2015 and 2016, there are only two companies, NXChain and First Bitcoin Capital, that changed their names, previously known as AgriVest Americas and Grand Paracaraima Gold respectively. In 2017, there are 11 companies who then change their names, and 12 in 2018.

Summary statistics for companies defined to have partaken in 'crypto-exuberant' behaviour through the use of 'blockchain' or 'cryptocurrency' in their name are presented in an accompanying online Appendix along with comparative summary statistics for the identified set of comparable corporate name-changing companies. When comparing the two groups of company announcements, those who have utilised cryptocurrency and blockchain when naming are found to have on average higher returns, yet more volatile returns with mean returns of -0.0081% and a standard deviation of 5.1575%. Further, such companies exhibit far more substantial extreme returns (where evidence is provided of one-day price decreases of 52.8% and increases of 57.7% when compared to -15.9% and 16.9% in non-cryptocurrency companies respectively), that are associated with skewness and kurtosis in excess of three times that of other non-cryptocurrency-based company names. Such a result indicates that companies that partake in the use of cryptocurrency-based naming practices are found to be substantially riskier shares to purchase when compared to other companies that have changed their corporate name for other types of reasons.

There have also been two companies who have actually changed their name twice, in both cases from a non-crypto-exuberant name to a crypto-exuberant name and then back again. For example, in August 2018, Focused Capital II Corp. announced its intention on the TSX Venture Exchange to change its name to Fortress Blockchain Corp., clearly positioning its corporate identity to be further associated with the growing blockchain and cryptocurrency markets. During this transaction, the company issued 71.2 million common shares and signalled its intention to begin trading on the TSXV under the ticker 'FORT'. In a largely unanticipated move, in April 2019, Fortress Blockchain then applied to the TSX Venture Exchange to change its name to Fortress Technologies Inc. while continuing to use the same ticker. This situation is one of the two cases within the dataset of a company retracting on its decision to partake in crypto-exuberant behaviour.

While considering the above examples, there are a number of companies whose use of blockchain and cryptocurrency naming changes merit particular attention. Long Island Iced Tea Corp. is one of the most famous companies to employ a crypto-exuberant naming strategy when changing their corporate identity to Long Blockchain Corp. in 2017. The stock price then sharply increased almost 300% stating that it was 'shifting its primary corporate focus' from tea to distributed-ledger technology. In 2019, it has been announced through warrants in the United States that the FBI is looking for evidence of insider trading and securities fraud connected to Long Island Iced Tea stock, where two men related to a separate company, were arrested for securities fraud[5]. There have also been broad accusations

[5] In September 2018, The SEC announced charges against a group of 10 individuals and their associated entities for long-running fraudulent schemes that brought in over $27 million. The SEC called those charged 'micro-cap fraudsters' in a press release. The initial evidence was provided by a CNBC investigation in February 2018, which identified a number of serious issues with regards to the company's SEC filings, in particular, issues with regards to the cancellation of annual meetings, the sales of stock by company insiders soon after the company's name change, dilutive share issuances on favourable terms to large investors, confusing SEC filings and evidence that a major shareholder was selling shares while everyone else was buying. In July 2019, it was reported that according to a request for a search warrant, the FBI was also searching for evidence of securities fraud. According to the warrant, FBI agents linked Long Blockchain Corp. to a separate fraud case involving securities fraud at separate firm. Two individuals were also identified as being involved in insider trading with Long Blockchain Corp. The FBI had previously warned investors that it was facing the risk of being de-listed as the SEC believed the firm 'made a series of public statements designed to mislead investors and to take advantage of general investor interest in bitcoin and blockchain

about the presence of a ‘pump-and-dump’ scheme, where promoters buy a cheap stock, start hyping it to investors with eye-catching claims, then sell their own holdings during the resulting mania, hopefully securing a profit before the stock comes crashing down. Based on a number of text messages that the FBI has since uncovered, they are interested in a person known as ‘Eric W’ in a series of messages, where the accused person owned approximately 15% of the shares in Long Island Iced Tea at the time that the company’s name was changed.

There is further investigation into the use of an investor relations program to develop hype around the company during this time. Riot Blockchain was also investigated throughout 2018 and 2019 by the SEC. It had previously changed its name from Bioptix, where its previous business practices were based on the development of veterinary products patent and developing new ways to test for disease. Under Section 8e of the Securities Act of 1933, if the SEC thinks that the registration statement contained ‘any untrue statement’ or omitted any ‘material facts,’ it may issue a stop order suspending the effectiveness of the registration statement. The company did make an investment in a cryptocurrency exchange in September and two months later did purchase a company that has cryptocurrency mining equipment, but paying more than $11 million for equipment reportedly valued at approximately $2 million as stated within SEC filings.

The filings also consider a number of very significant factors of interest including: 1) annual meetings that are postponed at the last minute; 2) insider selling soon after the name change; and 3) dilutive issuances on favourable terms to large investors. Further investigation identified one specific person of interest, who filed two 13Ds, including one in January 2017 that shows he/she owned 11.19% of the company, but his/her ownership dropped to less than 2 percent of outstanding common stock along with a small number of warrants in the time period immediately after the corporate name change. His/her purchase price ranged from $2.77 to $5.32 per share, according to the list of trades he/she provided to

technology’. The FBI warrant stated that, in the encrypted messages those investigated, these persons of interest had discussed what appears to be confidential information regarding the company.

the SEC in 2017, until the total investment dropped below the 5% threshold for SEC filing when the stock had already climbed above \$20.

While not explicitly identified to be under current investigation, some other companies with no other apparent technological investment have also participated in such crypto-exuberant behaviour. Vapetek Inc., who previously made batteries and liquid for electronic cigarettes, shifted its business practices to mine virtual currencies. Similarly, Croe, which sold women's fitness clothing before, changed its name to The Crypto Company, while Rich Cigars Inc., who produced and sold cigars before, changed its name to Intercontinental Technology Inc. The stated companies act as an example of the diversity of the companies that have taken part in such crypto-exuberant behaviour.

4. Methodology

4.1. Impact of name changes on firms' profitability and financing structure

In the first stage of our research, we test hypotheses H1 and H2 assuming that unlike regular name changes, crypto- and blockchain-related name changes signal that the company is about to enter a highly speculative business area. Therefore, profitability of the company might get hurt and its access to debt financing might get harder. To work on the above mentioned hypotheses, we use quarterly balance sheet and income statement data for the period between Q4 of 2017 and Q2 of 2019, adding up to 7 quarters in total. All data comes from Thomson Reuters Datastream. In our notations, FL_t represents financial leverage calculated by company's debt to equity at the end of quarter t and NI_t represents the net income in quarter t.

We construct control variables subject to three sets of stock characteristics. All variables are updated every quarter unless otherwise stated. The first set is associated with historical return patterns; (i) Size: Natural logarithm of the firm's market capitalisation by the end of last quarter, (ii) Book to Market (B/M) Ratio: Book-to-market ratio by the end of last quarter, (iii) MOM_{-1Q}: Cumulative return over the last quarter, (iv) $MOM_{[-4Q,-1Q]}$:

Cumulative three quarters' return preceding the last quarter, and (v) Beta: Beta is obtained from the regression of the firm's monthly returns over the last 2 years on the monthly market returns over the same period; i.e., $r_i - r_f = \alpha + \beta(r_M - r_f) + \epsilon$.

The second set is associated with liquidity and transaction costs; (vi) Price: Natural logarithm of the stock price by the end of each quarter, (vii) Turnover (TRN): Turnover ratio over the last quarter, and (viii) Amihud: Amihud ratio over the last quarter. Finally, the third set of stock characteristics is associated with prudence; (ix) Age: Natural logarithm of the number of quarters that the company is listed on the exchange, (x) Dividend Yield (DY): Dividend yield over the last quarter, (xi) Index: A dummy variable equal to 1 if the firm is included in the benchmark index and 0 otherwise, and (xii) Volatility (VOL): Standard deviation of monthly returns in the last two years. Therefore, we use 12 stock characteristics as control variables in total. To examine the effects of name changes on a company's profitability (H_1) and financial leverage (H_2), we run the following panel regression in equation (1) using two-way clustered standard errors.

$$Y_{t+1} = \alpha + \beta X_t + \gamma Name_t + \epsilon_t \tag{1}$$

In this model, Y is either the NI or FL and X_t is the vector of 12 stock characteristics described above. On the other hand, $Name_t$ is either: i) a dummy variable taking the value 0 if the company changed its name to a non-crypto related identity in quarter t, or ii) a dummy variable taking the value 1 if the company changed its name to a crypto related identity in quarter t. In each of the 7 quarters, we winsorize all variables (both dependent and independent) except the index and name change dummies in the cross-section by two levels from both upper and lower tails to get rid of the outlier effect without removing any observation.

4.2. Does there exist a persistent crypto-exuberance-based naming premium?

In the second stage of our research, we conduct a thorough investigation of the cumulative abnormal returns for each company and the average cumulative abnormal returns in the aftermath of a name change relating to either blockchain or cryptocurrency. Abnormal returns are calculated as the companies' returns minus that of the exchange on which the company trades. We have subdivided companies into two distinct groups. The first group is composed of those companies that have changed their name to incorporate blockchain and cryptocurrency, defined as being primarily for speculative reasons. The second group is denoted as a 'normal' test group, comprising companies that have changed their name, but have not incorporated any crypto-exuberant behaviour in their marketing decision. Any substantial change in cumulative abnormal returns would provide evidence that there exists a premium for such speculative-behaviour supporting H3, a finding that would conduce quite strong reservations amongst regulators and policy-makers alike.

This analysis consists of three parts. First, we focus on specific difference between the above mentioned crypto-exuberant group and the 'normal' test group, to test both hypotheses H3 and H4. Specifically, to analyse the persistence of the naming premium, we consider 1, 3, 5, 10, 20, 30, 60, 90 and 180 business days after the name change announcements to ensure that results are comparable to the results reported by previous studies. Second, we analyse whether cumulative abnormal returns change over time, as defined by annual separation for the period between 2015 and 2019, and specifically during the bitcoin pricing bubble of 2017. This test provides evidence for H5. Third, we account for regional changes in CARs as a robustness test, providing further validation of overall and time-varying results on a country-by-country basis.

4.3. The volatility effects of corporate cryptocurrency announcements

Next, we set out to analyse as to whether the structure of associated volatility in the periods both before and after the designated announcement presents evidence of substantial change. We first statistically test as to whether there is an increase in unconditional variance of the company stocks' daily returns (and the corresponding excess returns over the market they are traded in) after announcements for various time periods by utilising a common variance inequality test. We then dig deeper by building upon the GARCH-family to understand the volatility dynamics of crypto-exuberance based on naming behaviour in the conditional variances. At this stage, a number of goodness-of-fit testing procedures identified the EGARCH(1,1) model as the best selected to identify specific volatility changes in the companies' returns, thus we exercise our analysis using this model.[6] We express the variance equation of our EGARCH model as follows:

$$\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta\ln(h_{t-1}^2) + D_t \tag{2}$$

Here, we include an additional D_t term in equation (2) in our analysis to provide a coefficient relating to the observed conditional volatility in the subsequent days following each event for each of our investigated companies. Before we proceed with the EGARCH analysis, we mitigate exogenous effects which can be completed through the inclusion of the returns of traditional financial products in the mean equation of the EGARCH(1,1) methodology as displayed in equation (3).

$$r_t = a_0 + b_1 r_{t-1} + b_2 Dom.Ind_t + \varepsilon_t \tag{3}$$

The volatility sourced in shocks that are incorporated in the returns of traditional finan-

[6]EGARCH exploits information contained in realised measures of volatility while providing a flexible leverage function that accounts for return-volatility dependence. While remaining in a GARCH-like modelling framework and estimation convenience, the model allows independent return and volatility shock and this dual shock nature leaves a room for the establishment of a variance risk premium. In our selection, other competitive models included EGARCH, TGARCH, Asymmetric Power ARCH (APARCH), Component GARCH (CGARCH) and the Asymmetric Component GARCH (ACGARCH). The optimal model is chosen according to three information criteria, namely the Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ).

cial markets is therefore considered in the volatility estimation of the selected structure. In equation (3), r_{t-1} represents the lagged value of the observed company returns. $Dom.Ind_t$ is the returns of the benchmark index where the stock is traded, and represents the interaction between the selected company returns and the corresponding domestic market index.

4.4. Analysing potential contagion effects: A DCC-EGARCH methodology

The next stage develops on the channels through which such cryptocurrency volatility conduced through naming rights could influence other more traditional financial markets, and indeed, potentially unwilling and unsuspecting traders of such financial products. However, we are also concerned with changes in such contagion pathways between corporate entities. It is important to identify as to whether companies who had traditionally little or no involvement with blockchain or cryptocurrency markets had observed structural changes in their interactions with both their domestic exchanges and cryptocurrency markets.[7] For example, a company who had changed their name from that which did not identify as a blockchain or cryptocurrency-related company to one that does thereafter, could therefore theoretically experience a sharp change in dynamic correlations, perhaps also indicate that the company is being treated differently by investors in the aftermath of changed perceptions of corporate risk-tolerance, supporting hypothesis H6.

We must specifically analyse as to whether investors, who perceive these companies to have changed in terms of their perceived high-risk behaviour. To consider the contagion effects, we use the popular dynamic conditional correlation (DCC) model of Engle [2002]. We first let $r_t = [r_{1,t}, ..., r_{n,t}]'$ be the vector of financial time series returns and $\varepsilon_t = [\varepsilon_{1,t}, ..., \varepsilon_{n,t}]'$ be the vector of return residuals obtained after the filtration by equation (3). Let $h_{i,t}$ be the corresponding conditional volatilities obtained from a univariate EGARCH process.

[7] To represent the value of the cryptocurrency markets, we use the price of Pantera Capital which is the oldest and biggest crypto hedge fund in the world, and mostly preferred by institutional investors and retail investors with very high net worth. The reason of this selection instead of various available cryptocurrency indices is because the latter is strictly dominated by the movements of bitcoin due to its excessive market cap relative to other coins. However, in the case of the selected crypto fund, the investment in bitcoin is limited by a certain value, therefore it is a better representative of the whole coin market.

Assume that $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}[\varepsilon_t \varepsilon_t'] = H_t$, where $E_t[\cdot]$ is the conditional expectation on $\varepsilon_t, \varepsilon_{t-1}, \ldots$. The asset conditional covariance matrix H_t can be written as

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{4}$$

where $R_t = [\rho_{ij,t}]$ is the asset conditional correlation matrix and the diagonal matrix of the asset conditional variances is given by $D_t = diag(h_{1,t}, ..., h_{n,t})$. Engle [2002] models the right hand side of equation (4) rather than H_t directly and proposes the dynamic correlation structure

$$\begin{aligned} R_t &= \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2}, \\ Q_t &= (1 - a - b)S + a u_{t-1} u_{t-1}' + b Q_{t-1}, \end{aligned} \tag{5}$$

where $Q_t \equiv [q_{ij,t}]$, $u_t = [u_{1,t}, ..., u_{n,t}]'$ and $u_{i,t}$ is the transformed residuals i.e. $u_{i,t} = \varepsilon_{i,t}/h_{i,t}$, $S \equiv [s_{ij}] = E[u_t u_t']$ is the $n \times n$ unconditional covariance matrix of u_t, $Q_t^* = diag\{Q_t\}$ and a, b are non-negative scalars satisfying $a + b < 1$. The parameters of the DCC model are estimated by using the quasi-maximum likelihood method with respect to the log-likelihood function, and according to the two-stage procedure.

4.5. The information flows and price discovery following cryptocurrency-related announcements

In the final stage of our analysis, after developing on arguments surrounding pricing premiums, changing volatility dynamics and behavioural differences in the contagion effects between the observed companies and cryptocurrency markets, we analyse as to whether there has been a substantial change in both the information flow and structures underlying price discovery relationships between the name-changing companies and cryptocurrency markets. Fundamentally, such companies are clearly seeking to absorb elevated risk through the inclusion of naming similarities with these new high-risk products. However, while some companies have defined their primary business practice to be already heavily-influenced by cryptocurrency market dynamics, it is important to clarify as to whether investor perceptions shifted accordingly with the elevated levels of crypto-exuberance that thereafter exist.

There are two standard measures of price discovery commonly employed in the literature: the Hasbrouck [1995] Information Share (IS) and the Gonzalo and Granger [1995] Component Share (CS) measure. Hasbrouck [1995] demonstrates that the contribution of a price series to price discovery (the 'information share') can be measured by the proportion of the variance in the common efficient price innovations that is explained by innovations in that price series. Gonzalo and Granger [1995] decompose a cointegrated price series into a permanent component and a temporary component using error correction coefficients. The permanent component is interpreted as the common efficient price, the temporary component reflects deviations from the efficient price caused by trading fractions. We estimate IS and CS, as developed by Hauptfleisch et al. [2016] using the error correction parameters and variance-covariance of the error terms from the Vector Error Correction Model (VECM):

$$\Delta_{p1,t} = \alpha_1(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{200} \gamma_i \Delta p_{1,t-i} + \sum_{j=1}^{200} \delta_j \Delta p_{2,t-j} + \varepsilon_{1,t} \tag{6}$$

$$\Delta_{p2,t} = \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{200} \varphi_k \Delta p_{1,t-k} + \sum_{m=1}^{200} \phi_m \Delta p_{2,t-m} + \varepsilon_{2,t} \tag{7}$$

where $\Delta p_{i,t}$ is the change in the log price $(p_{i,t})$ of the asset traded in market i at time t. The next stage is to obtain the component shares from the normalised orthogonal coefficients to the vector of error correction, or:

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}; CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2} \tag{8}$$

Given the covariance matrix of the reduced form VECM error terms[8] where:

[8] $\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$ and its Cholesky factorisation, $\Omega = MM'$.

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{\frac{1}{2}} \end{pmatrix} \tag{9}$$

we calculate the IS using:

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} \tag{10}$$

$$IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} \tag{11}$$

Recent studies show that IS and CS are sensitive to the relative level of noise in each market, they measure a combination of leadership in impounding new information and the relative level of noise in the price series from each market. The measures tend to overstate the price discovery contribution of the less noisy market. An appropriate combination of IS and CS cancels out dependence on noise (Yan and Zivot [2010], Putniņš [2013]). The combined measure is known as the Information Leadership Share (ILS) which is calculated as:

$$ILS_1 = \frac{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right|}{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|} \text{ and } ILS_2 = \frac{\left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|}{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|} \tag{12}$$

We estimate all three price discovery metrics, noting that they measure different aspects of price discovery.

5. Results

5.1. The impact of name changes on firms' profitability and access to debt financing

We report the estimated coefficients of equation (1) in Table 2 for the cases of NI and FL with respect to crypto related (upper panel) and non-crypto related (lower panel) name changes respectively. For each of the explained variables, we first regress separately on variables related to i) historical return patterns ($M1$ column), ii) liquidity and transaction costs ($M2$ column), and iii) prudence ($M3$ column). Finally, M_{all} column shows the results when all control variables are used as explanatory.

Insert Table 2 about here

In Table 2, we first notice that whether we use only a sub-group of control variables or all of them at the same time, there is consistency in the signs of the explanatory variables with a very small amount of exceptions for both net income and financial leverage analysis. This shows the reliability of the results. Regarding the determinants of profitability (net income), crypto and non-crypto related name changing companies differ substantially with respect to selected control variables. According to the M_{all} analysis, except the insignificant market cap and short-term momentum variables, effect of all variables on profitability differ with respect to either sign or insignificance between the different types of name changes.

In this analysis, the main variable of interest is the dummy variable $Name_t$ and according to our findings, the coefficient of this dummy supports our hypothesis H_1. In the upper panel, the significant negative dummy coefficient implies that when a company changes its name to something cryptocurrency or blockchain related, its profitability significantly decreases. However, the lower panel of Table 2 shows us that in the case regular name changes, we do not observe such a phenomenon; i.e., regular name change has no significant impact on profitability. Regarding the determinants of financial leverage, the two type of name changing companies have more common factors compared to the case of net income.

For example, according to the M_{all} column, variables such as market cap, book-to-market ratio, short-term momentum, beta, stock price, age, and volatility have no significant impact on the leverage; whereas turnover and Amihud ratio are both significant and have impact in the same direction. More importantly, the coefficient of the name change dummy differs significantly when we compare the type of name changes. Supporting our hypothesis H_2, whether we take only a sub-group or all control variables as explanatory, the crypto-related name change dummy is significantly negative, indicating that such a name change has a dampening effect on financial leverage of the company. However, the insignificant dummy coefficient in the case of regular name changes shows us that there is no such effect for this group.

5.1.1. Robustness of the findings

To check the robustness of the findings above, we try alternative variations of equation (1) and start with estimating the following equation (13). The motivation is to bring a dynamic perspective to the analysis by focusing on not the levels but the change in the levels of net income and leverage.

$$\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta X_t + \gamma Name_t + \epsilon_t \tag{13}$$

Insert Table 3 about here

The estimated coefficients are displayed in Table 3. At this stage, we prefer to only focus on the main variable of interest and discuss the findings on the name change dummy variable. Accordingly, the findings strongly support both our hypotheses H_1 and H_2 whether we use only a sub-group or all control variables at the same time to explain the changes in the dependent variables of quarterly net income change or leverage change. In the case of regular name changes, there is not a single significant name change dummy coefficient. However, in the case of crypto and blockchain-related name changes, the estimations generate all significant negative coefficients at the 1% level ranging from -0.978 to -0.866 (-0.789 to -0.166) for the change in net income (financial leverage), depending on the selected control group. We take our robustness analysis even one step further and instead of a separate analysis for the two types of name changes, we employ analogous regression of equations (1) and (13) in the new equations (14) and (15), respectively. These models allow us to control for the two type of name changes at the same time and the estimated coefficients are reported in Tables 4 and 5.

$$Y_{t+1} = \alpha + \beta X_t + \gamma_1 CryptoName_t + \gamma_2 RegularName_t + \epsilon_t \tag{14}$$

Insert Table 4 about here

At this stage, to support our hypotheses H_1 and H_2, the expectations of the dummy coefficient signs in the last two equations above are the same as in the previous analysis, and the findings almost perfectly fit. In the case of equation (14), without an exception, all dummy name change coefficients are significantly negative for both income and the leverage. Surprisingly though, the same dummy for the regular name changes produces some positive significant results.

$$\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta X_t + \gamma_1 CryptoName_t + \gamma_2 RegularName_t + \epsilon_t \tag{15}$$

Insert Table 5 about here

Regarding equation (15), the estimated coefficients back our hypotheses up even stronger. Besides having all significant negative dummy coefficients with respect to crypto and blockchain-related name changes, there is not a single significant dummy coefficient for the regular company name changes. Overall, our findings imply that a name change related to blockchain or cryptocurrency concepts is a potential signal for joining a speculative business and might have a negative effect on company's both business activities and access to debt. However, a regular name change does have no such effect as expected.

5.2. Cumulative abnormal returns due to name changes

We then investigate the cumulative abnormal returns for each company and the average cumulative abnormal returns in the aftermath of a name change relating to either blockchain or cryptocurrency. Any substantial change in cumulative abnormal returns would provide substantial evidence that there exists a premium for such speculative-behaviour. We first analyse the overall premiums that exist between companies that both partake and do not partake in crypto-exuberant naming behaviours. There are quite substantial, and somewhat worrying results from a regulatory perspective.

In Table 6, standard name changing behaviour is found to be associated with a 5.50% premium in the first day after the date of implementation, but this premium is found not to persist and quickly reverts to a negligible 0.03% premium 20 days after the announcement date. However, crypto-exuberant name changes are found to be associated with a 32.06% premium in the day following the announcement of the name change. Further, the premium persists for an exceptional period of time, with a 4.99% premium evident 20 days after the announcement, and 3.49% 30 days later. In the entire six month period analysed after each event, the crypto-exuberant announcement resulted in a permanent 0.78% premium. Such evidence should cause concern for regulators and policy-makers as there exists both a significant and substantial reward from partaking in such questionable corporate decision-making.

Insert Table 6 about here

We next examine whether such cumulative abnormal returns have varied or indeed persisted over time. While the first evidence of crypto-exuberant behaviour that was identified was in 2015, we examine the average results on an annual basis to find that there has existed a substantial and persistent premium since companies started to use the words 'blockchain' and 'cryptocurrency' in their names. The largest one-day premium was found to exist in 2017 where companies experienced a 52.58% increase in share prices on the day of a name change. While there exist substantial premiums on an annual basis throughout all of the years examined, there appears to be quite a significant difference in the way that such premiums are found to persist. We observe that premiums in 2015 are 4.57% 10 days after the announcement, while in 2017 they are 8.79%. In all cases examined, substantial premiums are found to persist for between 10 and 20 days after each event on an annual basis.

Finally, in Table 6 we examine as to whether there exist geographical differences in identified crypto-exuberant premiums and as to whether there are differences in the behaviour of name changes during periods denoted to have possessed cryptocurrency bubbles (H_5). While such companies were identified in 10 different countries, we have only presented results where there were both crypto-exuberant and non-crypto exuberant events identified. This group consists of Canada, Germany, South Korea and the United States. Crypto-exuberant naming premiums are found to be substantially lower when compared to other countries in Germany (+9.08%), but the identified premium is still substantially higher than non-cryptocurrency based name changes. The largest one-day premium was identified in the United States (+40.42%). While German and South Korean premiums are both identified to be substantial and positive for 10 days after the name-change announcement, the premium reverts to zero thereafter. However, in both Canada and the United States, the crypto-exuberant premium persists for six months after the announcement date. Further, these premiums are also substantially above the cumulative abnormal returns of companies that have not partaken in crypto-exuberant name changes.

Overall, we present evidence of substantial premiums associated with corporate name-changes that are found to persist over time (up to a quarter in general) and across the geographical regions examined. Further, when specifically investigating as to whether there are differentials in name premiums for companies that have announced their name changes during bitcoin bubbles (as defined by the work of Corbet et al. [2018]), we find two distinct results. First, there is clearly a pronounced and sustained premium for companies denoted as to have partaken in crypto-exuberant behaviour when compared to those companies that have not, adding further robustness to earlier results. The magnitude of this premium is in excess of four and five times that of non-crypto exuberant companies.

Secondly, there is a further premium, as identified solely within those companies identified as crypto-exuberant, who made the decision to change their corporate name during the period of time in late-2017 and early-2018 when bitcoin prices continued to grow to almost $20,000. Such results indicate acceptance of hypothesis H_5, showing that the underlying price growth of bitcoin appears to have generated a further premium for companies that decided to change their name during this period of time. However, this premium was solely identified for those companies denoted as developing blockchain and cryptocurrency technology.

5.2.1. Robustness test to support the CAR findings

In this part, we take a different perspective on the CAR analysis and instead of working with the abnormal returns directly, we analyse the results of the following regression.

$$r_t = a_0 + b_1 r_{t-1} + b_2 Dom.Ind_t + D_t + \varepsilon_t \tag{16}$$

As usual, in equation (16), r_{t-1} represents the lagged value of the observed company returns. $Dom.Ind_t$ is the returns of the benchmark index where the stock is traded and it helps us to control for the market effect. D_t is a dummy term to provide a coefficient relating to the observed return changes in the subsequent 1-5-10-20-40-60-all days following name changes for our sample companies. The results of these models are displayed in Table 7 for three different after event horizon (5, 40 and 60 days) as a demonstration. In this table, only the results for the companies with a significant positive D_t term is presented.

Insert Table 7 about here

On the other hand, Table 8 presents the overall results without getting into specific company analysis. In Panel A of Table 8, we see that only one week following the name changes, more than 80% of the companies with new crypto-related names experience a positive premium, however in the case of regular name changes, this percentage is slightly above 50%. When we focus on only the significant premium earnings as displayed in Panel B of Table 8, the picture is even more striking. Accordingly, one week after, around 35% of the companies with crypto-related name changes have significant excess return premiums, which is close to 4 times the percentage value that we see in the case of regular changes.

Insert Table 8 about here

When we consider longer periods such as a quarter and after, the positive premium effect substantially decreases for both the cases of regular and crypto-related name changes. In the next quarter following the name changes, 13% of the companies with crypto-related names still have significant premium, that is more than 6 times of the same ratio for the companies with other type of name changes. In the longest-run period we consider after the name changes, 29% (45%) of the companies with crypto-related (regular) name changes still have the positive premium. However, if we consider only the significant positive excess premiums, none of the companies manage to have it after a quarter. In essence, we see that crypto-related name changes create a hype in the stock prices of these companies, much more emphasised than the case of regular name changing companies. However, it is clear that this hype is not sustained for a very long time and the resulting premium vanishes after a quarter.

5.3. The volatility effects of corporate cryptocurrency announcements

We next analyse the structural changes in stock price volatility and in particular, try to see as to whether there is evidence of substantial differences based on the type of name changes that has been made? Our analysis first focuses on the unconditional volatility; i.e., the standard deviation of the returns. For this, we apply an F-test to statistically see whether there has been a significant increase in unconditional volatility after the two types of name changes. We use several time windows covering 10-20-40-60-all days before and after name changes to analyse the unconditional volatility dynamics both in the short and long-run. Additionally, we redo the same analysis using also daily excess returns (stock return minus the domestic market return) to control for the aggregate market fluctuations. The results are provided in Table 9.

Insert Table 9 about here

According to the Panel A (Panel B) of Table 9, around 65% (45%) of the crypto related name changing companies have experienced a (significant) rise in their stock returns' unconditional volatility in just 10 days. This rise is mostly preserved even after a quarter following the name changes. However, in the case of regular name changes, only 43% of the companies experience a higher volatility after 10 days (see Panel A of Table 9) and more importantly, in only 31% percent of them are significant according to Panel B of Table 9. In the case of regular name changes, the percentage of companies experiencing a significant higher volatility after name changes never exceeds 35%, however in the case of crypto-related name changes, this percentage never drops below 45% no matter what time frame we select.

A logical argument against the findings above could state that the changes in the unconditional volatility might be due to the aggregate market fluctuations, not the company name changes. To challenge this, we instead focus on the (significant) increases in the unconditional volatilities of the excess returns over the market and results are provided in Panel C (Panel D) of Table 9. In this case, the main results are almost the same as those in the previous analysis. Accordingly, 65% (48%) of the crypto-related name changing companies experience a (significant) increase in their unconditional volatility of excess returns in a 10 day frame, and this increase is preserved even after a quarter. In the case of regular name changes, only 39% (27%) of the companies experience (significant) increase in unconditional volatilites of their excess returns and we don't observe a noteworthy change in this percentage when we consider different time frames. Overall, analysis suggests that cryptocurrency and blockchain related name changes create much more significant increases in the unconditional volatility of the company stock prices compared to those with regular name changes.

5.3.1. Robustness test to support the findings on unconditional volatility changes

The analysis of unconditional volatility presents striking results however the subject requires extensive investigation since the stylised fact of volatility clustering (which is common for almost all financial time series) might shadow the true nature of the price fluctuations. In order to deal with this, we employ the EGARCH model in equation (2) after filtering the returns by equation (3). To examine the conditional volatility changes in different time frames following name changes, we use various dummy lengths in equation (2), including 1-10-20-40-60-all days after the name changes.

For a demonstration, Tables 10 and 11 respectively display the companies with significant increase in their conditional volatility in the short- (5 days) and long-run (all days) after name changes, with upper (lower) panels in both tables exhibit the results for crypto-related (regular) name changes.

Insert Tables 10 and 11 about here

On the other hand, Table 12 presents an overall picture of the analysis on conditional variance changes. In the very next day following name changes, 68% (29%) of the crypto-related name changing companies experience (significant) increase in their conditional volatility. Whereas this (significant) increase is very limited with 29% (16%) in the case of regular name changes. Considering longer periods following name changes also presents important differences between the effects of two different type of name changes.

For example, in the longest period we consider, 58% of the crypto-related companies have still increased conditional volatilities, whereas in the case of regular name changes, this number is 26%, below the half of the value that we see for crypto-related name changes. When we focus on only significant increases, the difference between these two cases becomes even more imbalanced. Accordingly, in the case of crypto-related name changes, 26% of the companies have significantly increased conditional volatilities in the longest-run we consider. For the case of regular name changes, according to Table 12, only less than 4% of these companies still experience a significantly higher conditional volatility in the long-run.

Insert Table 12 about here

Both our analysis on unconditional and conditional volatility show us that cyrpto-related name changes create much more excessive volatility in companies' stock prices compared to the regular name changes. Moreover, this effect tends to be permanent as it does not disappear mostly after a quarter and even longer periods than that.

5.4. Analysing potential contagion effects: A DCC-EGARCH methodology

Through the use of a DCC-EGARCH methodology, we specifically analyse the dynamic relationships between companies who have partaken in crypto-exuberant naming practices and those that changed their corporate identity for other reasons with both cryptocurrency markets and the domestic indices on which they trade. These dynamic relationships are presented in Figure 1. In the top panel, we observe the relationships in the 50 business day period both before and after the official corporate name change.

Insert Figure 1 about here

We can clearly identify that traditional companies show little difference of change in correlations with cryptocurrency markets in the period thereafter, however, companies that partake in crypto-exuberant name changes through the addition of words such as 'blockchain' and 'cryptocurrency' exhibit a sharp and extended period of growth in correlation with cryptocurrency markets. This presents quite an interesting result. While considering that some of the companies in our sample have no prior association with blockchain, cryptocurrency or indeed technology of any form, we observe that such companies become more associated with high-risk cryptocurrency markets. This particular result also presents evidence that investors in such companies could perhaps be substantially under-pricing the true risk associated with their investment.

To verify this result, we also employ the following regression to identify whether such a result can be observed in a statistically significant manner, where we model a dummy variable that takes a value of unity in the period after the announcement of the name change based on the dynamic correlations between the companies analysed:

$$\rho_t = \alpha + \beta \rho_{t-1} + D_t + \varepsilon_t \tag{17}$$

The relationship between crypto-exuberant companies and cryptocurrency markets is found to increase by $+0.0329$, with this result being significant at the 1% level. However, standard company name changes and cryptocurrency markets present an insignificant result of -0.0063. Further, the relationship between both crypto-exuberant and non-crypto-exuberant name changes are found to be both insignificantly related with the domestic indices on which they trade, a result that validates the dynamic correlations presented in the upper panel of Figure 1.

Applying the same methodology to the dynamic correlations between the companies and the domestic indices on which the company trades presents insignificant results of $+0.0004$ for crypto-exuberant companies and $+0.0006$ for non-crypto-exuberant companies which validates the results identified in the lower panel of Figure 1 where we identified no change in the relationships between these markets after changing corporate identity.

In Figure 2, we focus on some selected dynamic correlations between individual companies that did not previously possess any relationship with blockchain, cryptocurrency or technological development. For example, Hive Blockchain Technologies Ltd. was previously known as Leeta Gold Corp., while Online Blockchain Plc. was previously known as On-line Plc. with primary business interests in international and information processing business. Further, Blockchain Worldwide was previously known as Stapleton Capital who had firmly been identified as a telecoms business, while Blockchain Group Co Ltd. was previously known as Ping Shan Famous Tea, a Hong-Kong-based company that firmly operated in the tea products manufacturing industry.

Insert Figure 2 about here

We can clearly observe the sharp increases in DCC-EGARCH-calculated dynamic correlations in the period immediately after the decision to change corporate identity. Through the use of the above regression methodology, we find that all results are statistically significant at the 1% level, where sharp increases are presented for Hive Blockchain Technology (+0.4719), Online Blockchain PLC (+0.2109), Blockchain Group Co Ltd (+0.3516) and Blockchain Worldwide (+0.7245). Overall, these results indicate that there was a sharp increase in the correlations between crypto-exuberant name-changing companies and cryptocurrency markets in the period after the decision to restructure their corporate identity. However, there is no significant change in the correlations between these companies and the exchanges on which they trade.

5.5. The information flows and price discovery following cryptocurrency-related announcements

The final stage of our analysis focuses specifically on the flow of information and price discovery between markets. As evident in our DCC-EGARCH methodology, companies who partake in crypto-exuberant name changes are found to become more correlated in pricing performance with cryptocurrency markets. We therefore in this section attempt to establish the sources of information flows and price discovery between the selected markets. We present the results of the calculated information flows in our online Appendix, we observe the differences in price discovery between crypto-exuberant name changing companies and stock markets, presenting the differences between the same companies and cryptocurrency markets. The coefficients for information share, reverse-information share, the component share of information and the information leadership share are presented for the periods both before and after the corporate name change.

The prevalent result is defined to be based on the domestic stock index influencing the selected corporate entity being analysed. It is identified that most companies exhibit a substantial reduction in information flow and price discovery sourced from the index on which the company trades to the company being analysed. The most substantial changes of information flow are identified in companies such as Blockchain Power Trust Unit, Blockchain Group Co Ltd. and Atlas Blockchain. We also observe the same companies' information share relationships with cryptocurrency markets. While we have identified a reduction in information flows from domestic stock indices on the identified crypto-exuberant name changes companies, we then identify sharp increases in information flow and the direction of price discovery sourced within cryptocurrency markets and the same companies.

This result provides further validation that companies that exhibit such crypto-exuberant decision-making practices are found to somewhat decouple from traditional information flows to instead source such price discovery in high-risk cryptocurrency markets. This could serve as quite a contentious action to those investors who have selected to make their investment-decisions based on the information that was provided. As to whether the corporate entity actually develops such blockchain or cryptocurrency technology acts as a significant source of asymmetric information, generating both regulatory and legal concerns surrounding the transparency provided by key decision-makers within such companies. When observing crypto-exuberant companies, earlier findings are further validated when considering the relationships between companies that have changed their names for alternative reasons.

We identify a substantial variation in the flow of information and price discovery from cryptocurrency markets on non-crypto-exuberant name changing companies. Within this context, there is no discernible, singular direction of change with the breadth and scale of the change in direction presenting no evidence of a singular path. This same level of ambiguous information flow is also presented when considering the interactions between the same standard name changing companies and the exchanges on which they trade. The scale and direction of such interactions do not present evidence of a clearly identified pattern. This result adds further support to the above analysis where crypto-exuberant companies present clear increased relationships with cryptocurrency markets while simultaneous decreased relationships with domestic indices are further identified.

Finally, Table 13 displays the net average changes in price discovery as designated by type of company and both cryptocurrency markets and the domestic exchanges on which the companies trade. In the top-panel, we observe the relationships between both types of name changing companies and stock markets. The relationships are observed to be the net change from the exchange to the company.

Insert Table 13 about here

We clearly observe that in the aftermath of a naming change, companies that partake in crypto-exuberant name changes are found to obtain reduced information flows and price discovery from their own domestic exchanges, while the companies who conduct standard, non-cryptocurrency-related name changes are found to increase moderately.

Meanwhile, in the lower-panel of Table 13, we observe clear evidence of sharply increased information flows and price discovery sourced in the pricing of cryptocurrency markets on that of crypto-exuberant naming companies. This analysis presents substantial evidence that supports the earlier DCC-EGARCH findings that companies that partake in such crypto-exuberant behaviour change not only in public perceptions through a changed corporate identity, however, there exists both changes in the underlying financial characteristics of the company along with sharp behavioural changes in the way the company's share prices interact with other areas of financial markets.

Within both the internal and external financial structures of these companies, we provide multiple pieces of evidence showing that companies that partake in crypto-exuberant naming practices receive not only a premium that is both substantial and persistent, but are found to be substantially more correlated with cryptocurrency markets than that of their own domestic indices. The existence of such a price premium in associated with the shifting dynamics of non-technological corporate entities to exhibit the risk behaviour or high-risk cryptocurrency markets should be of concern to both regulators and policy-makers alike.

This premium is found to be robust throughout the period identified to be most likely to contain a pricing bubble in late 2017. Further, companies who made the decision to change their names with a rationale defined to partake in crypto-exuberance during this period experienced a substantial additional premium during this bubble-phase, in comparison to companies who changed their names for reasons defined to be of non-crypto-exuberance. It is in this manner that the corporate use of blockchain and cryptocurrency technology has been influenced by information asymmetry and transparency through corporate use of crypto-exuberance.

6. Conclusions

This research examined the relationship between corporate performance and the decision to change corporate identity in a crypto-exuberant manner, namely through the addition of words such as ‘blockchain‘ and ‘cryptocurrency‘ in the corporate name. This trend has become more frequent since 2017, and has been particularly concerning due to the large number of companies with no previous experience or association with indeed, any form of technological development prior to their decision to partake in such crypto-exuberant behaviour.

It must be further considered that the broad shift in direction within our identified blockchain and cryptocurrency-based companies has yet to present evidence of any major developments within their respective fields. While a number of companies have been investigated in the United States by both the FBI and SEC for potential financial malpractice such as ‘pump-and-dumps‘ and ‘insider trading,‘ the focus of our research surrounds the presence of asymmetric information and the reduction, or indeed obscurity, of corporate transparency through the incorporation of blockchain technology in such companies.

For both clarity and robustness, we have selected a number of well-known methodologies on which to base our analysis of such crypto-exuberant behaviours. We primarily focus on changes in the firms’ profitability and financing structure in the aftermath of corporate name changes. The selected hypotheses develop on the fact that unlike regular name changes, the selection of blockchain and cryptocurrencies acts as a signal of entry into a highly speculative business area, a fact that should be considered to directly relate to the corporate risk-taking preferences. Further, we consider specific changes within three key sets of stock characteristics, first based on historical returns patterns, secondly with liquidity and transaction costs, and finally with corporate prudence.

The second-stage of our analysis should warrant specific interest to policy-makers. We focus on the presence of a crypto-exuberant-premium in the period after name change implementation. Any positive premium would indicate that there exist financial rewards from partaking in such name changing behaviour, even if the company does not continue to adapt blockchain nor cryptocurrency-based technology. The following methodologies therefore consider the perceptions of investors as to the selected new directions taking by the decision-makers within these corporations. We first set out to establish as to whether such companies have become inherently more risky, which is considered to be a condition in their new-found associated with high-risk cryptocurrency markets. Then we focus on the interactions between these companies and both their industrial peers and cryptocurrency markets in terms of contagion effects and the flow of information and price discovery. Any significant changes in this final methodology indicate that both investors and financial markets have re-evaluated their perceptions of the business practices of these companies and consider their new technological consideration to be somewhat excessive when compared to their historic performance.

The results of our research are fourfold in scope. First, we find evidence of substantial internal differentials between companies who utilise corporate crypto-exuberant name changes when compared to a group of non-blockchain or cryptocurrency-related corporate rebranding. Specifically, we find that crypto-related name changes directly harm a company's short-term level of profitability when compared to the selected 'normal' test group, while crypto-related companies are also found to decrease their financial leverage in the following quarter after announcement, a result that is not present for the comparable 'normal' test group.

Second, we find evidence of substantial crypto-exuberant pricing premiums, acting as a reward for companies that utilise such questionable tactics. Not only are such premiums substantial, but they are also found to persist for up to six months after, a result that is robust over time and across multiple geographic regions.

Third, we find substantial evidence of sharp increases in the volatility of share price performance, which is not a surprising result when considering that the identified corporations are self-selecting when incorporating high-risk blockchain and cryptocurrency technology as a central theme of their perceived business image. However, we further find that the dynamic correlations of such volatility have also shifted substantially in the aftermath of such name changes. The identified crypto-exuberant companies are found to decrease in dynamic correlations with the domestic exchange on which they trade, while simultaneously increase in dynamic correlations with cryptocurrency markets, a results that verifies the changing investor perceptions of such a decision to change corporate identity in this manner.

In a fourth key results, we verify such changing investor perceptions of these companies through the identification that both the information flows and sources of price discovery have also changed substantially, where such companies are perceived to be more associated with higher-risk cryptocurrency markets than that of previously identified contagion channels, results that are validated by both significance and the presence of robustness testing procedures. Such direct financial impacts are quite a surprising outcome, as in the majority of companies identified, there have been no structural changes in the company with the exception of the change in corporate identity.

Such results should concern investors, regulators and policy-makers alike. While the decision to partake in such high-risk investment strategies would be expected to be associated with more volatile payoff structures, unwilling investors in companies who have partaken in such crypto-exuberant name changing behaviour are found, through both robust and significant methodologies to have incorporated extremely volatile characteristics into their financial performance, both internally-observed through their own internal accounts, and externally-observed through both their associated and relative stock market performance. Only the key decision-makers within the company know for certain as to whether the new corporate association with blockchain and cryptocurrency will ever develop to generate technological developments. The use of such crypto-exuberant behaviours appears to have generated information asymmetry and has masked the transparency of such corporations, necessitating immediate investigations into the true rationale behind the decisions to utilise such behaviours. While perhaps not explicitly illegal in some jurisdictions, such decision making warrants further inquisition from investors and regulators alike.

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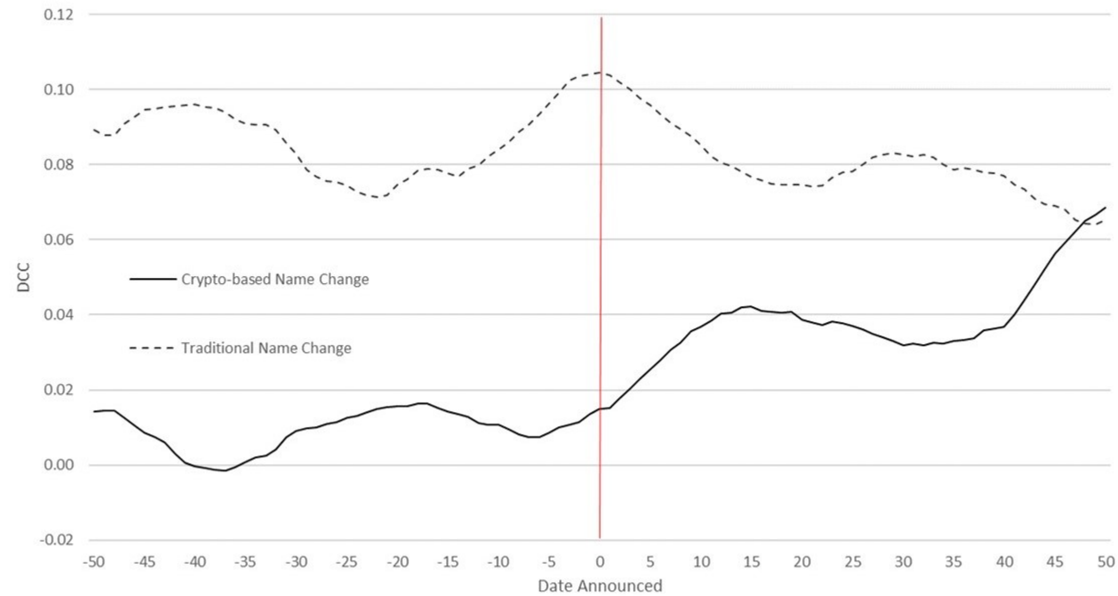
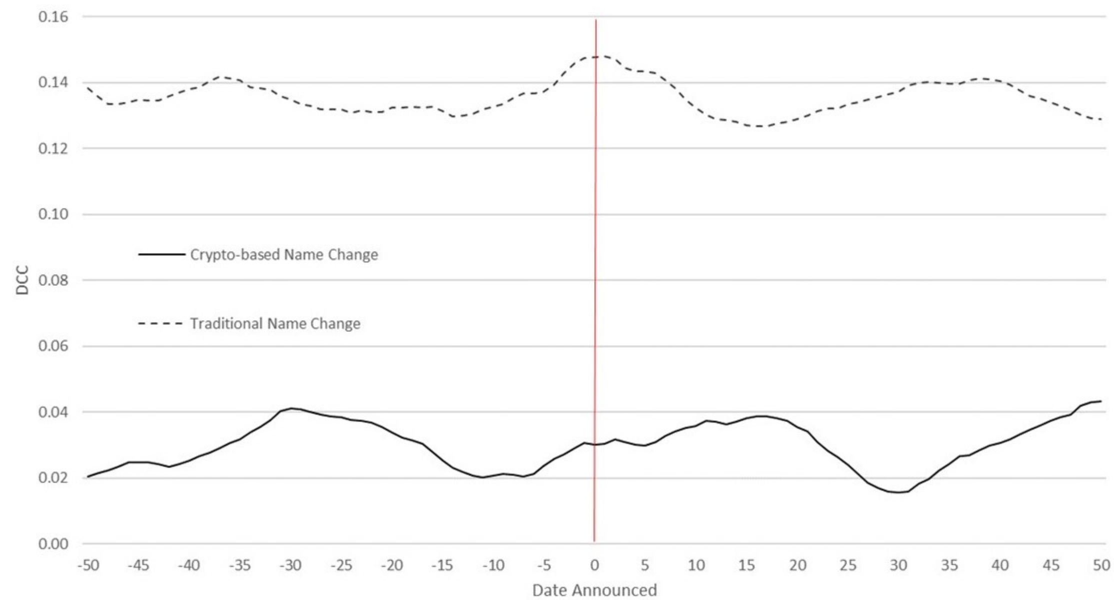
Figure 1: Dynamic correlations as separated by the selected type of name change

a) Dynamic correlations with cryptocurrency markets

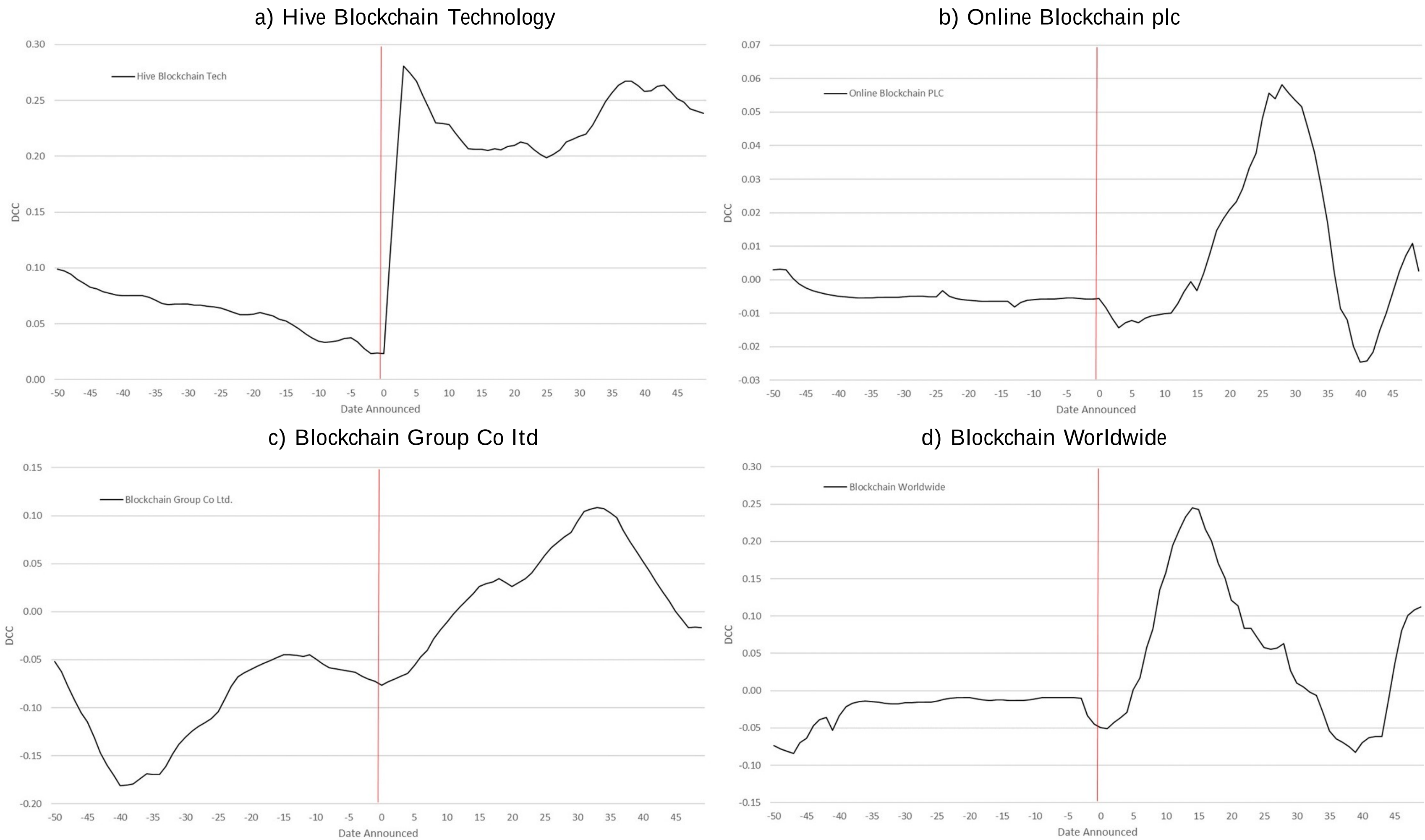


b) Dynamic correlations with the domestic index



Note: The above figure shows the five-day moving average of dynamic correlations as calculated through the use of the specified DCC-EGARCH methodology. The top figure presents the dynamic correlations between both companies who did and did not partake in crypto-exuberant naming practices and that of cryptocurrency markets. The bottom figure represents the same correlations with the domestic indices on which the companies trade.

Figure 2: Selected corporate dynamic correlations due to name changes



Note: The above figures represent selected one hundred day dynamic correlations between a selected sub-set of companies in the above analysis and our selected cryptocurrency fund.

Table 1: Name changing companies between December 2015 and June 2019

Denoted as Crypto-Exuberant Name Changes				Non-Cryptocurrency Based Name Changes							
Company	Ticker	Country	Date	Company	Ticker	Country	Date	Company	Ticker	Country	Date
NXChain	NXCN	US	30/12/2015	Duoback	073190.KQ	S.Korea	28/03/2018	Poly Developments	600048.SS	HK	12/09/2018
First Bit. Capital	BITCF	Canada	15/09/2016	SM Entertainment	041510.KQ	S.Korea	28/03/2018	Neptune Wellness	TWSI.PK	Canada	19/09/2018
Future FinTech	FTFT.O	US	09/06/2017	ANTN	050320.KQ	S.Korea	28/03/2018	Paddy Power Bet.	PPB.I	Ireland	08/10/2018
Hive Blockchain	HIVE	Canada	15/09/2017	Enerzent	041590.KQ	S.Korea	29/03/2018	RPT Realty	RPT.N	US	31/10/2018
360 Blockchain	CODE.CD	Canada	04/10/2017	HI Special Purpose	217500.KQ	S.Korea	30/03/2018	Coingeek Tech Ltd	SQR	Canada	30/11/2018
Riot Blockchain	RIOT	US	04/10/2017	Sangsangin	038540.KQ	S.Korea	30/03/2018	Coca-Cola	COKE.O	US	02/01/2019
Blockch. Power T.	BPWR	Canada	21/10/2017	Joongang Living	051980.KQ	S.Korea	30/03/2018	Ignite Int Brands	ALQ.CD	Canada	08/01/2019
Online Blockchain	OBC	UK	26/10/2017	Royal Helium	RHC.V	Canada	24/04/2018	TC Energy	TRP.TO	Canada	09/01/2019
UBI Blockchain	UBIA	US	12/12/2017	Item 9 Labs	INLB	US	26/04/2018	Pinnacle Renewable	PL	Canada	09/01/2019
Nodechain Inc	NODC	US	17/12/2017	Sun Metals	SUNM	Canada	04/05/2018	Zen Graphene	ZEN	Canada	15/01/2019
Long Blockchain	LBCC	US	21/12/2017	Exantas Capital	RSO	US	10/05/2018	Fidelity Minerals	FMN	Canada	23/01/2019
Bitcoin Group	ADE	Germany	21/12/2017	Absa Group	ABSP	S.Africa	18/05/2018	Hankook	000240	HK	24/01/2019
The Crypto Co.	CRCW	US	22/12/2017	Grid Metals	GRDM	Canada	06/06/2018	Adventus Mining	ADZN.V	Canada	24/01/2019
Blockchain Group	0364	S.Korea	31/12/2017	Atlantis Resources	SAE.L	UK	15/06/2018	Apollo Capital	AINV.O	Poland	24/01/2019
Bitcoin Services	BTSC	US	12/01/2018	ValOre Metals	VO	Canada	26/06/2018	Monarch Gold	MQR	Canada	26/01/2019
Blockchain W.	BLOC	UK	22/01/2018	Oxurion	OXUR	Belgium	27/06/2018	Central Wealth	0139	HK	01/02/2019
iMining Blockchain	IMIN	Canada	18/04/2018	Western Ur. & V.	WUC	Canada	03/07/2018	CGI	GIB	US	01/02/2019
Crypto.com	MCO	HK	06/07/2018	Relay Medical	CHX	Canada	04/07/2018	Norra Metals	OK.V	Canada	08/02/2019
Atlas Blockchain	AKE	Canada	25/07/2018	HC Group Inc	2280	HK	09/07/2018	Great Panther Silv.	GPL	US	11/02/2019
Litelink Tech	LLT	Canada	16/08/2018	Pepkor Holdings	PPH	S.Africa	20/07/2018	Summit Properties	SMTP	UK	20/02/2019
Fortress Blockchain	FORT	Canada	20/08/2018	Cheng Mei	4960	Taiwan	21/07/2018	DNO North Sea	DNO	Norway	15/05/2019
Cascadia Blockch.	CK.CD	Canada	07/09/2018	XPEL Inc	DAP	Canada	25/07/2018	Experion Holdings	EXP	Canada	06/06/2019
Blockchain Infra.	1NT.D	Germany	28/09/2018	Prestige C. Health	PBH	US	03/08/2018	ZTR Acquisition	ZTR.V	Canada	21/06/2019
Blockchain Lab	DOA.WA	Poland	20/11/2018	Depomed	ASRT	US	08/08/2018	Mogo	MOGO	Canada	22/06/2019
Design Blockch.	NVFY	US	20/11/2018	Expedeon AG	EXN	Germany	09/08/2018	Stagezero	SZLS	Canada	25/06/2019
Interbit Ltd	BLT	Canada	09/01/2019	Peruvian Metals	DRV.V	Canada	29/08/2018				
Highwood Oil	HOCL	Canada	28/01/2019								
Global Gaming	GGAM	Canada	07/02/2019								
Codebase Ventures	CODE.CD	Canada	15/02/2019								
Fortress Tech	FORT	Canada	12/03/2019								
Metaverse Capital	FORK	Canada	22/05/2019								

Note: The above table was developed utilising a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords: "name change", "corporate identity", "cryptocurrency", "digital currency", "blockchain", "distributed ledger", "cryptography", "cryptographic ledger", "digital ledger", "altcoin" and "cryptocurrency exchange" under traditional corporate announcements. To obtain a viable observation, a single data observation must be present across the three search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. Forums, social media and bespoke news websites were omitted from the search. 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 (three announcements in total) are denoted as active on the following Monday morning. To omit issues with regards to stock illiquidity which presents substantial issue with regards to our selected methodology, we eliminated all companies that possessed at least three-separately identified consecutive two-hour periods with zero trading volumes at time periods with no stated stock market issues. Such a rule eliminated companies that presented many significant periods of illiquidity and poor trading quality which would distort the analysis on their market variables. We further supported the robustness of our final sample to eliminate exceptionally small companies through the inclusion of a rule that any company that is part of the final sample must have possessed a market capitalisation of above $50 million (USD), as calculated by the dollar-converted market capitalisation during the period of analysis.

Table 2: Modelling the impact of name changes on firms' profitability and financing structure (Regression analysis, crypto-exuberant vs. non-crypto-exuberant separate, level regression)

Crypto-Exuberant.	Income				Leverage			
Model Specification	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Market Cap	-0.8242			-0.2325	-0.0179			-0.0236
	(1.4670)			(0.1590)	(0.0231)			(0.0252)
Book to Market Ratio	1.0903			0.1139	-0.0014			0.0030
	(0.7680)			(0.8102)	(0.0121)			(0.0128)
Returns (Q_{t-1})	-0.0110			-0.0114	0.0000			0.0000
	(0.0140)			(0.0141)	(0.0002)			(0.0002)
Returns (Q_{t-4} - Q_{t-2})	0.0021			0.0019***	0.0000***			0.0000***
	(0.0025)			(0.0025)	(0.0000)			(0.0000)
β	0.9928			0.1126*	-0.0375			-0.0193
	(2.4382)			(0.2584)	(0.0384)			(0.0410)
Stock Price		0.7991***		1.0612***		0.0309		0.0152
		(0.2398)		(0.2656)		(0.0380)		(0.0421)
Turnover Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Amihud Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Age			0.1255*	0.1788***			-0.2390**	-0.1979
			(0.0736)	(0.0811)			(0.1155)	(0.1285)
Dividend Yield			-0.3210	-0.4413			0.9612	1.4661*
			(0.4252)	(0.4891)			(0.6670)	(0.7754)
Benchmark Index			0.0000***	0.0000***			0.0000***	0.0000***
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Volatility			-0.4071	-0.2412			-0.1286	-0.1378
			(0.7091)	(0.7245)			(0.1112)	(0.1148)
γ	-0.6666***	-0.6792***	-0.7419***	-0.7112***	-0.6152***	-0.3837***	-0.9915***	-0.4552***
	(0.1312)	(0.1288)	(0.1320)	(0.1391)	(0.0207)	(0.0038)	(0.2070)	(0.0220)

Non-Crypto-Exuberant.	Income				Leverage			
Model Specification	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Market Cap	-0.7224*			-0.4382	0.0229			0.0228
	(0.4285)			(0.5905)	(0.1033)			(0.1435)
Book to Market Ratio	1.0109***			0.4832***	0.0000			-0.0002
	(0.3268)			(0.1747)	(0.0002)			(0.0004)
Returns (Q_{t-1})	1.3842*			1.2686	-0.0016			-0.0016
	(1.0121)			(1.3265)	(0.0032)			(0.0032)
Returns (Q_{t-4} - Q_{t-2})	0.4154			0.5184	-0.0002			-0.0003
	(0.3596)			(0.3666)	(0.0009)			(0.0009)
β	0.5054***			-0.3891*	-0.2230			-0.1683
	(0.1463)			(0.1536)	(0.3528)			(0.3733)
Stock Price		0.3361		-0.9879		0.0218		0.1198
		(0.7304)		(1.0726)		(0.1617)		(0.2607)
Turnover Ratio		0.0000***		0.0000***		0.0000		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Amihud Ratio		0.0000		0.0000		0.0000***		0.0000***
		(0.0001)		(0.0001)		(0.0000)		(0.0000)
Age			0.7966***	0.6050**			0.1430	-0.0282
			(0.2861)	(0.3153)			(0.6939)	(0.7664)
Dividend Yield			1.0587***	0.6628***			0.0014	0.0162
			(0.0795)	(0.1648)			(0.0193)	(0.0401)
Benchmark Index			-0.3106	-0.4002			-0.6369	-1.2100
			(0.5173)	(0.6376)			(1.2546)	(1.5499)
Volatility			0.6319**	-0.2296*			-0.0003	0.0004
			(0.2679)	(0.2873)			(0.0065)	(0.0070)
γ	-0.1852	-0.0906	-0.1490	-0.1916	-0.5305	-0.4805	-0.5244	-0.4588
	(1.0972)	(1.2009)	(1.0808)	(1.1112)	(2.6458)	(2.6551)	(2.6186)	(2.7009)

Note: Table displays the results of the panel regression $Y_{t+1} = \alpha + \beta X_t + \gamma Name_t + \epsilon_t$ where Y is either net income or financial leverage, and X_t are the control set. In the upper (lower) panel, $Name_t$ is a dummy variable taking the value 1 if the company changed its name to a crypto (non-crypto) related identity in quarter t, otherwise 0. The values in the parentheses are standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 3: Modelling the impact of name changes on firms' profitability and financing structure (Regression analysis, crypto-exuberant vs. non-crypto-exuberant separate, robustness test, first-difference regression)

Crypto-Exuberant	Income				Leverage			
Model Specification	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Market Cap	-1.2975			-2.6914*	-0.0180			-0.0248
	(1.4932)			(1.6167)	(0.0236)			(0.0258)
Book to Market Ratio	1.1727			0.1197	-0.0007			0.0028
	(0.7794)			(0.8232)	(0.0123)			(0.0131)
Returns (Q_{t-1})	-0.0107			-0.0102	0.0000			0.0000
	(0.0154)			(0.0155)	(0.0002)			(0.0002)
Returns (Q_{t-4} - Q_{t-2})	0.0014			0.0012	0.0000			0.0000***
	(0.0025)			(0.0025)	(0.0000)			(0.0000)
β	1.0343			0.8539	-0.0412			-0.0231
	(2.5332)			(2.6881)	(0.0401)			(0.0428)
Stock Price		0.7632***		1.0719***		0.0363		0.0227
		(0.2494)		(0.0276)		(0.0396)		(0.0440)
Turnover Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Amihud Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Age			1.5693**	2.1088**			-0.2219*	-0.1727
			(0.7639)	(0.8467)			(0.1205)	(0.1349)
Dividend Yield			-0.4437	-0.5354			1.0978*	1.6588**
			(0.4546)	(0.5237)			(0.7174)	(0.8347)
Benchmark Index			0.0000***	0.0000***			0.0000***	0.0000***
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Volatility			-0.5432	-0.4164			-0.1483	-0.1607
			(0.7550)	(0.7723)			(0.1192)	(0.1231)
γ	-0.8661***	-0.8885***	-0.9782***	-0.9485***	-0.3809***	-0.7890***	-0.2634***	-0.1660***
	(0.1446)	(0.1421)	(0.1463)	(0.1543)	(0.0229)	(0.0226)	(0.0231)	(0.0246)

Non-Crypto-Exuberant.	Income				Leverage			
Model Specification	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Market Cap	-0.7378			-0.5859	0.0108			0.0286
	(0.5579)			(0.7545)	(0.1348)			(0.1839)
Book to Market Ratio	1.0601***			0.4032*	-0.0001			-0.0002
	(0.4556)			(0.2109)	(0.0002)			(0.0005)
Returns (Q_{t-1})	1.1957*			2.4865	-0.0053			-0.0052
	(0.6623)			(0.6559)	(0.0160)			(0.0161)
Returns (Q_{t-4} - Q_{t-2})	0.2449			0.5797	-0.0019			-0.0025
	(0.2136)			(0.2152)	(0.0052)			(0.0052)
β	0.1662			0.7114	-0.3987			-0.2316
	(0.2422)			(0.2576)	(0.5852)			(0.6282)
Stock Price		0.4105***		-0.8743		0.0065		0.1987
		(0.0948)		(1.4341)		(0.2102)		(0.3496)
Turnover Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Amihud Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Age			-0.4805	0.4025			-0.1407	-0.2911
			(0.3902)	(0.4383)			(0.9502)	(1.0685)
Dividend Yield			1.0935**	0.7694			0.0020	0.0184
			(0.9533)	(1.9641)			(0.0232)	(0.0479)
Benchmark Index			-0.1998	-0.6558			-1.1807	-1.9282
			(0.6421)	(0.7952)			(1.5634)	(1.9386)
Volatility			0.9574	-0.9250			-0.0001	0.0007
			(3.1850)	(3.4046)			(0.0078)	(0.0083)
γ	-0.8169	-1.3365	-1.1001	-1.5141	-0.8158	-0.9002	-0.6638	-0.9870
	(1.1891)	(1.2673)	(1.1493)	(1.2043)	(2.8728)	(2.8080)	(2.7983)	(2.9362)

Note: Table displays the results of the panel regression $\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta X_t + \gamma Name_t + \epsilon_t$ where Y is either net income or financial leverage, and X_t are the control set. In the upper (lower) panel, $Name_t$ is a dummy variable taking the value 1 if the company changed its name to a crypto (non-crypto) related identity in quarter t, otherwise 0. The values in the parentheses are standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 4: Modelling the impact of name changes on firms' profitability, financing structure, and insider ownership (Regression analysis, crypto-exuberant vs. non-crypto-exuberant together, robustness test, level regression)

Dep. Var: Full Sample	Income				Leverage				% Ownership			
Model Specification	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Market Cap	-0.6504**			-0.5591*	0.0285			0.0174	0.0711*			0.1358***
	(0.3569)			(0.4694)	(0.0863)			(0.1144)	(0.0429)			(0.0557)
Book to Market Ratio	1.0062**			4.6803***	0.0000			-0.0002	0.0001			0.0001
	(0.5563)			(1.5362)	(0.0001)			(0.0004)	(0.0001)			(0.0002)
Returns (Q_{t-1})	1.0167			0.5077	-0.0008			-0.0008	0.0034			0.0029***
	(0.7574)			(7.6135)	(0.0018)			(0.0019)	(0.0009)			(0.0009)
Returns (Q_{t-4} - Q_{t-2})	0.2273			0.0395	-0.0001			-0.0001	0.0001			0.0000
	(1.3268)			(1.3346)	(0.0003)			(0.0003)	(0.0002)			(0.0002)
β	0.3979***			0.7515***	-0.2005			-0.1762	-0.3573***			-0.1621
	(0.1083)			(0.1124)	(0.2617)			(0.2739)	(0.1300)			(0.1335)
Stock Price	1.7704	2.9887***		0.7517		0.0366		0.0891		0.4375***		0.2906***
	(1.4045)	(0.6043)		(0.8276)		(0.1340)		(0.2017)		(0.0814)		(0.0983)
Turnover Ratio		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Amihud Ratio		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Age		-0.1391	0.1935	0.2722			0.1377	0.1004			-1.6564***	-1.9117***
		(0.1532)	(0.2262)	(0.2425)			(0.5499)	(0.5910)			(0.2730)	(0.2880)
Dividend Yield			1.0586	0.6738***			0.0015	0.0145			0.0147**	0.0035
			(0.7097)	(0.1457)			(0.0173)	(0.0355)			(0.0086)	(0.0173)
Benchmark Index			-0.2978	-0.5154			-0.3477	-0.8590			0.5746	-1.4242***
			(0.4432)	(0.5427)			(1.0776)	(1.3224)			(0.5341)	(0.6443)
Volatility			0.6737***	0.2253			-0.0003	0.0003			0.0017	0.0006
			(0.2395)	(0.2562)			(0.0058)	(0.0062)			(0.0029)	(0.0030)
γ_{crypto}	-0.3220***	-0.1616	-0.8621***	-0.2826***	-0.5374***	-0.6196***	-0.7293***	-0.6237***	3.4136***	2.7295***	2.8938***	2.5364***
	(0.1105)	(0.1206)	(0.1394)	(0.0141)	(0.1950)	(0.1959)	(0.1389)	(0.1344)	(0.6862)	(0.6722)	(0.6794)	(0.6744)
γ_{normal}	0.8768	0.7134***	0.1959***	0.2230***	-0.3709	-0.2897	-0.2701	-0.2316	2.4662***	2.7412***	2.8860***	2.6402***
	(0.6547)	(0.2232)	(0.1086)	(0.1117)	(0.2670)	(0.2673)	(0.2640)	(0.2723)	(1.3261)	(1.3153)	(1.3081)	(1.3267)

Note: Table displays the results of the panel regression $Y_{t+1} = \alpha + \beta X_t + \gamma_1 CryptoName_t + \gamma_2 RegularName_t + \epsilon_t$ where Y is either net income, financial leverage or insider ownership ratio, and X_t are the control set. $CryptoName_t$ ($RegularName_t$) is a dummy variable taking the value 1 if the company changed its name to a crypto (non-crypto) related identity in quarter t, otherwise 0. The values in the parentheses are standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 5: Modelling the impact of name changes on firms' profitability and financing structure (Regression analysis, crypto-exuberant vs. non-crypto-exuberant together, robustness test, first-difference regression)

Dep. Var: Full Sample	Income				Leverage			
Model Specification	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Market Cap	-0.6262*			-0.3321	0.0297			0.0104
	(0.3688)			(0.4832)	(0.0893)			(0.1182)
Book to Market Ratio	0.0105***			0.0038**	0.0000			-0.0002
	(0.0006)			(0.0016)	(0.0001)			(0.0004)
Returns (Q_{t-1})	0.0007			0.0002	-0.0005			-0.0005
	(0.0084)			(0.0084)	(0.0020)			(0.0021)
Returns (Q_{t-4} - Q_{t-2})	0.0002			0.0000	-0.0001			-0.0001
	(0.0014)			(0.0014)	(0.0003)			(0.0003)
β	0.6476			0.2781	-0.1989**			-0.1612
	(1.1310)			(1.1711)	(0.2740)			(0.2865)
Stock Price		-0.3156		-0.5747		0.0565		0.1349
		(0.6351)		(0.8646)		(0.1408)		(0.2115)
Turnover Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Amihud Ratio		0.0000***		0.0000***		0.0000***		0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Age			0.0199	0.1471			0.1436	0.1029
			(2.3621)	(2.5387)			(0.5772)	(0.6211)
Dividend Yield			1.0932***	0.7878***			0.0014	0.0162
			(0.0745)	(0.1519)			(0.0182)	(0.0372)
Benchmark Index			-0.2551	-0.7261			-0.3986	-1.0029
			(4.6228)	(5.6564)			(1.1296)	(1.3839)
Volatility			0.0102	-0.0081			-0.0003	0.0004
			(0.0251)	(0.0268)			(0.0061)	(0.0066)
$\gamma_{regular}$	-0.5361	-0.2379	-0.6135	-0.5982	-0.5808	-0.5651	-0.5290	-0.5328
	(0.9273)	(1.0071)	(0.9123)	(0.9277)	(2.2464)	(2.2328)	(2.2292)	(2.2699)

Note: Table displays the results of the regression $\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta X_t + \gamma_1 CryptoName_t + \gamma_2 RegularName_t + \epsilon_t$ where Y is either net income or financial leverage, and X_t are the control set. $CryptoName_t$ ($RegularName_t$) is a dummy variable taking the value 1 if the company changed its name to a crypto (non-crypto) related identity in quarter t, otherwise 0. The values in the parentheses are standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 6: Cumulative Abnormal Returns in the aftermath of name changing announcements

	Days after a Name Change Announcement								
Description	1 Day	3 Days	5 Days	10 Days	20 Days	30 Days	60 Days	90 Days	180 Days
Overall CARs									
Crypto-based name	32.06%	15.84%	8.82%	4.57%	4.99%	3.49%	1.92%	1.27%	0.78%
Normal name change	5.50%	1.41%	0.65%	0.57%	0.03%	0.16%	-0.04%	-0.02%	0.05%
Combined effects	15.85%	7.04%	3.83%	2.13%	1.97%	1.46%	0.73%	0.48%	0.34%
CARs over time (crypto-exuberant companies only)									
2015	24.94%	15.75%	7.87%	4.57%	2.30%	4.68%	3.51%	3.05%	1.46%
2016	15.74%	5.79%	3.08%	1.62%	-1.23%	4.75%	4.42%	5.35%	4.64%
2017	52.58%	29.13%	17.20%	8.79%	10.69%	6.96%	3.65%	2.24%	1.09%
2018	17.25%	7.90%	3.28%	1.56%	0.95%	0.38%	0.26%	0.16%	0.36%
2019	20.09%	3.47%	2.24%	1.65%	2.00%	1.53%	0.60%	0.20%	0.06%
Selected geographic dispersion of CARs									
Canadian crypto-name	35.79%	12.52%	6.11%	3.96%	2.91%	2.42%	1.39%	0.92%	0.83%
Canadian name change	9.37%	2.88%	1.29%	1.07%	0.03%	0.21%	0.03%	0.02%	0.07%
US crypto-name	40.42%	21.59%	13.10%	5.63%	10.24%	6.69%	3.42%	2.29%	1.23%
US name change	2.99%	-0.85%	-0.23%	-0.05%	-0.05%	0.02%	-0.11%	0.05%	0.35%
S.Korean crypto-name	18.23%	6.18%	4.57%	1.06%	-1.05%	-0.68%	0.48%	0.23%	-0.32%
S.Korean name change	4.45%	1.68%	0.75%	0.65%	0.17%	0.13%	-0.08%	-0.02%	-0.05%
German crypto-name	9.08%	2.35%	2.65%	2.19%	0.99%	-0.23%	0.38%	0.19%	0.08%
German name change	1.33%	0.42%	0.36%	-0.03%	-0.15%	-0.79%	-0.49%	-0.41%	-0.22%
Behaviour during the defined cryptocurrency bubble (all companies, as per Corbet et al. [2018])									
Non-Crypto-Exuberant Companies									
Non-Bubble Period$^+$	6.30%	3.96%	2.30%	4.27%	3.32%	3.35%	3.10%	2.38%	1.24%
Bubble Period$^+$	7.14%	3.26%	1.58%	2.84%	3.23%	2.98%	1.11%	0.83%	0.72%
Crypto-Exuberant Companies									
Non-Bubble Period$^+$	14.96%	4.75%	2.38%	2.10%	2.37%	1.72%	0.89%	0.81%	0.64%
Bubble Period$^+$	30.03%	9.31%	7.41%	6.14%	7.78%	4.14%	5.43%	4.35%	3.57%

Note: Abnormal returns are calculated as the companies' returns less that of the exchange on which the company trades. We have subdivided such an analysis into two distinct groups. The first group is composed of those companies that have changed their name to incorporate blockchain and cryptocurrency, defined as being primarily for speculative reasons. The second group is denoted as a 'normal' test group, comprising companies that have changed their name, but have not incorporated any crypto-exuberant behaviour in their marketing decision. Any substantial change in cumulative abnormal returns would provide substantial evidence that there exists a premium for such speculative-behaviour, a finding that would conduce quite strong reservations amongst regulators and policy-makers alike. $^+$ indicates that a bubble has been defined in the market for bitcoin similar to that described by the work of Corbet et al. [2018].

Table 7: Companies with significant positive impact of cryptocurrency and blockchain related name changes on stock return's premium in the short- and long-run

Panel A: Five-day Dummy				
Crypto				
Company	const a_0	r_{t-1}	$Dom.Ind_t$	D_t^{5d}
Hive Blockchain Tech	0.0003	-0.0455	0.6465**	0.1688***
	(-0.8951)	(-7.326)	(0.0425)	(2.2982)
360 Blockchain Inc	-0.0006	-0.1269***	0.1316	0.0457*
	(0.4045)	(-1.7237)	(2.3612)	(11.8215)
Online Blockchain PLC	-0.0003	-0.1291***	0.2315	0.123***
	(-0.4168)	(-4.812)	(0.2758)	(1.9361)
UBI Blockchain	-0.0021	-0.0102	-1.9051**	0.2039***
	(-0.469)	(-4.9215)	(1.3677)	(11.3126)
Nodechain Inc	-0.0041	-0.0904**	-0.036	0.1046***
	(-0.615)	(-0.3852)	(-2.003)	(3.5422)
Long Blockchain Technology	0.0003	0.0721***	-0.0365	0.0389*
	(-1.3817)	(-2.1021)	(-0.0468)	(3.3633)
Blockchain Worldwide	-0.0009	-0.0621	-0.1672	0.0465***
	(0.2194)	(2.7114)	(-0.1011)	(1.7976)
iMining Blockchain	-0.0005	-0.0528**	0.3435	0.0468*
	(-0.7093)	(-1.3486)	(-0.3925)	(3.5932)
Blockchain Infrastructure Group AG	0.0009**	0.089*	0.0383	0.0185***
	(-0.3422)	(-2)	(0.6693)	(1.8251)
Blockchain Lab S.A.	0	0.0718***	0.036	0.0278**
	(2.2312)	(1.8226)	(0.3753)	(4.9353)
Metaverse Capital	-0.0049	-0.4172***	0.0874	0.0903**
	(0.021)	(2.7227)	(0.1767)	(2.1279)
Stock				
HI Special Purpose Acquisition	0.0001	0.0494	0.5687***	0.0093*
	(0.1481)	(1.6306)	(5.3034)	(1.7821)
Prestige Consumer Healthcare	-0.0002	-0.0283	0.8664***	0.0076**
	(-0.9971)	(-1.1542)	(15.1171)	(2.1924)
Apollo Capital S.A.	-0.0002	-0.0361	0.3207***	0.0048*
	(-1.1184)	(-1.3949)	(7.9415)	(1.8703)
Norra Metals	-0.001	-0.1045***	-0.1857	0.05***
	(-1.1179)	(-3.9559)	(-0.5979)	(3.2377)
Stagezero Life Sciences	-0.0006	-0.0382	0.4133	0.0331*
	(-0.5687)	(-1.4482)	(1.065)	(1.7086)
Panel B: Forty-day Dummy				
Crypto				
Company	const a_0	r_{t-1}	$Dom.Ind_t$	D_t^{40d}
Hive Blockchain Tech	0.0001	0.0254	0.6973**	0.0276***
	(0.0878)	(0.9595)	(2.4547)	(5.389)
360 Blockchain Inc	-0.0009	-0.1278***	0.1276	0.0162*
	(-0.6203)	(-4.8435)	(0.2674)	(1.9169)
Riot Blockchain	-0.001	-0.0234	0.9007***	0.0089*
	(-1.2377)	(-0.8931)	(3.957)	(1.8057)
Blockchain Power Trust Unit	-0.0012	-0.1521***	-0.4015	0.0088*
	(-1.3877)	(-5.6063)	(-1.4131)	(1.7662)
Online Blockchain PLC	-0.0006	-0.0757***	0.2477	0.0249***
	(-0.8754)	(-2.8753)	(1.4227)	(6.386)
Blockchain Infrastructure Group AG	0.0008*	0.111**	0.0448	0.0036**
	(1.7492)	(2.232)	(0.4277)	(2.514)
Panel C: Sixty-day Dummy				
Crypto				
Company	const a_0	r_{t-1}	$Dom.Ind_t$	D_t^{60d}
Hive Blockchain Tech	0.0002	0.0355	0.7218**	0.0163***
	(0.1778)	(1.3441)	(2.5295)	(3.8683)
Riot Blockchain	-0.0012	-0.0261	0.8903***	0.0116***
	(-1.5149)	(-0.9943)	(3.9168)	(2.8546)
Online Blockchain PLC	-0.0005	-0.0629**	0.2424	0.0151***
	(-0.7667)	(-2.3891)	(1.3828)	(4.6942)
Highwood Oil Company	-0.0002	-0.1713	-0.362	0.0084*
	(-0.1231)	(-3.1447)	(-0.5087)	(1.822)

Note: This table presents the estimation results of the equation $r_t = a_0 + b_1 r_{t-1} + b_2 Dom.Ind_t + D_t + \varepsilon_t$. In this regression equation, r_{t-1} represents the lagged value of the observed company returns. $Dom.Ind_t$ is the returns of the benchmark index where the stock is traded. D_t is a dummy term to provide a coefficient relating to the observed return changes in the subsequent 5-40-60 days following each event for each of our investigated companies. Only the results for the companies with a significant positive D_t term is presented. The values in the parentheses are t-statistics. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 8: Number (percentage) of companies experiencing an increase in their stock returns' premium in the short and long-run after their name changes

Panel A: Positive dummy coefficient							
business area	D^{1d}	D_t^{5d}	D_t^{10d}	D_t^{20d}	D_t^{40d}	D_t^{60d}	D_t^{All}
Crypto	20 (64.52)	25 (80.65)	23 (74.19)	19 (61.29)	18 (58.06)	17 (54.84)	9 (29.03)
Stock	28 (54.9)	27 (52.94)	26 (50.98)	21 (41.18)	24 (47.06)	21 (41.18)	23 (45.1)

Panel B: Significant positive dummy coefficient							
business area	D^{1d}	D_t^{5d}	D_t^{10d}	D_t^{20d}	D_t^{40d}	D_t^{60d}	D_t^{All}
Crypto	7 (22.58)	11 (35.48)	9 (29.03)	7 (22.58)	6 (19.35)	4 (12.9)	0 (0)
Stock	5 (9.8)	5 (9.8)	5 (9.8)	0 (0)	0 (0)	1 (1.96)	0 (0)

Note: This table presents the overall results from the regression equation $r_t = a_0 + b_1 r_{t-1} + b_2 Dom.Ind_t + D_t + \varepsilon_t$ where r_{t-1} represents the lagged value of the observed company returns, $Dom.Ind_t$ is the returns of the benchmark index where the stock is traded, D_t is a dummy term to provide a coe□cient relating to the observed return changes in the subsequent 5-40-60 days following each event for each of our investigated companies. This shows the number of companies that experience an increase in their stock returns' premium after their name changes. The column headers show the number of days that we calculate the return premium after the name changes. In the table, the values in the parentheses are the percentage of companies within the sub-groups experiencing an increase in their stock returns' premium. Panel A (Panel B) reports the number of companies that experience a (significantly) higher return premium in their stocks.

Table 9: Number (percentage) of companies experiencing an increase in their stock returns' unconditional volatility in the short and long-run after their name changes

Panel A: Log-returns with higher variance					
business area	**[-10,+10]**	**[-20,+20]**	**[-40,+40]**	**[-60,+60]**	**[all pre-ann , all post-ann]**
crypto	19 (70.97)	19 (61.29)	21 (61.29)	20 (67.74)	16 (64.52)
stock	31 (43.14)	24 (37.25)	30 (37.25)	26 (41.18)	21 (39.22)
Panel B: Log-returns with significantly higher variance					
business area	**[-10,+10]**	**[-20,+20]**	**[-40,+40]**	**[-60,+60]**	**[all pre-ann , all post-ann]**
crypto	15 (48.39)	14 (45.16)	19 (61.29)	17 (54.84)	14 (45.16)
stock	16 (31.37)	14 (27.45)	18 (35.29)	17 (33.33)	16 (31.37)
Panel C: Excess log-returns with higher variance					
business area	**[-10,+10]**	**[-20,+20]**	**[-40,+40]**	**[-60,+60]**	**[all pre-ann , all post-ann]**
crypto	20(64.52)	19(61.29)	21(67.74)	20(64.52)	15(48.39)
stock	32(39.22)	27(37.25)	30(41.18)	27(39.22)	21(29.41)
Panel D: Excess log-returns with significantly higher variance					
business area	**[-10,+10]**	**[-20,+20]**	**[-40,+40]**	**[-60,+60]**	**[all pre-ann , all post-ann]**
crypto	15 (48.39)	14 (45.16)	18 (58.06)	17 (54.84)	14(45.16)
stock	14 (27.45)	12 (23.53)	16 (31.37)	16 (31.37)	16(31.37)

Note: This table shows the number (percentage) of companies that experience a higher unconditional volatility in their stock prices after name changes. The column headers show the unconditional volatility calculation periods in days before and after the name changes. In the table, the values in the parentheses are the percentage of companies within the sub-groups experiencing an increase in their stock returns' unconditional variances. Panel A (Panel B) reports the number of companies that experience a (significantly) higher variance in their stocks' daily returns. Panel C (Panel D) reports the number of companies that experience a (significantly) higher variance in their stocks' daily excess returns over the corresponding market returns.

Table 10: Regression results for significant increases in conditional volatility in the short-run (5 days) after their name changes

Company	a_0	r_{t-1}	$Dom.Ind_t$	ω	α	β	γ	D_t
Panel A: Crypto firms								
First Bitcoin Capital	-0.0009***	-0.219***	3.1157***	-0.0859***	0.0359	0.9742***	0.2401***	0.2245*
	(0.0002)	(0.033)	(0.6281)	(0.0287)	(0.0376)	(0.0059)	(0.0513)	(0.1293)
Hive Blockchain Tech	0.0003	-0.0089	0.6177	-7.3097***	-0.0457	-0.0252	-0.0042	4.4515***
	(0.0007)	(0.0166)	(0.5034)	(2.1288)	(0.0759)	(0.288)	(0.2066)	(1.508)
Blockchain Power Trust Unit	-0.0013	-0.1381***	-0.4108***	-0.1474***	-0.0591	0.9745***	0.1448***	0.4735*
	(0.0011)	(0.0359)	(0.0976)	(0.0112)	(0.041)	(0.0005)	(0.0366)	(0.2509)
Online Blockchain PLC	0*	-0.3805**	0.0177	-1.1531**	-0.1315	0.8241***	0.9168***	2.3667**
	(0)	(0.1772)	(0.0132)	(0.5607)	(0.1129)	(0.0486)	(0.1039)	(0.9994)
Long Blockchain Technology	-0.0007***	0.0227***	0.002***	-10***	0.0059	-0.6329*	0.1365***	3.0773***
	(0)	(0.0007)	(0.0001)	(2.316)	(0.073)	(0.34)	(0.0328)	(0.6443)
iMining Blockchain	-0.0041***	-0.0774***	1.587***	-0.8522***	-0.0953	0.8428***	0.1969**	0.4281**
	(0.0006)	(0.0279)	(0.418)	(0.0736)	(0.0692)	(0.0154)	(0.0975)	(0.1967)
Atlas Blockchain	-0.0029**	-0.0823***	2.3931**	-0.1032***	-0.002	0.9883***	-0.0575***	0.1993***
	(0.0012)	(0.0284)	(1.0132)	(0.0038)	(0.0036)	(0.214)	(0.0208)	(0.0322)
Blockchain Lab S.A.	-0.0015*	0.0287***	-0.0758*	-1.0193***	-0.0546	0.8468***	0.2752***	0.6271***
	(0.0009)	(0.006)	(0.0402)	(0.2646)	(0.035)	(0.0383)	(0.0507)	(0.1815)
Metaverse Capital	-0.0065	-0.3724***	-1.2033	-1.5493***	0.0958	0.684***	0.2841***	0.451***
	(0.0041)	(0.0713)	(2.3652)	(0.4994)	(0.1177)	(0.1002)	(0.0701)	(0.1741)
Panel B: Stock firms								
SM Entertainment	-0.0001*	0.0263	0.8275***	-0.9753***	-0.0316	0.8915***	0.1205***	0.1977**
	(0.0001)	(0.017)	(0.1069)	(0.3063)	(0.0387)	(0.0339)	(0.0415)	(0.0793)
Joongang Living Tech	-0.0005	0.0492	1.0139***	-0.9161	-0.0252	0.8758***	0.4541***	0.4949*
	(0.0008)	(0.0826)	(0.2603)	(0.8369)	(0.0623)	(0.1093)	(0.1704)	(0.2775)
Sun Metals	0	-0.4262	0	0.1122	-0.1055	0.9993***	0.7833	8.6516***
	(0.0002)	(0.3377)	(0.0001)	(0.3516)	(1.3447)	(0.0107)	(0.5101)	(1.2352)
Relay Medical Corp	-0.0011***	-0.2824***	-0.5522***	-1.1592*	0.0388	0.8336***	0.3897***	0.4563***
	(0.0002)	(0.0306)	(0.1183)	(0.6286)	(0.0584)	(0.0891)	(0.1164)	(0.1706)
Depomed	-0.0004	-0.0287	1.1966***	-1.1164***	-0.1496***	0.8646***	0.0925***	0.7637**
	(0.0004)	(0.0258)	(0.0931)	(0.0257)	(0.0397)	(0.0015)	(0.0276)	(0.3535)
Neptune Wellness Solutions	0	-0.0688**	0.5982***	-2.2683**	0.0196	0.723***	0.3271***	0.8101***
	(0.0002)	(0.0271)	(0.0599)	(0.9339)	(0.0397)	(0.1137)	(0.096)	(0.2656)
Paddy Power Betfair	0.0001	0.0693	0.5507***	-4.3553***	0.0652	0.5605***	0.3258**	0.8425***
	(0.0002)	(0.0667)	(0.1163)	(1.5077)	(0.0922)	(0.1537)	(0.1561)	(0.2486)
Ignite International Brands Ltd	0	-0.2333	0	0.1782	-0.1644	1***	0.354**	7.1302***
	(0.0002)	(0.825)	(0.0001)	(0.1467)	(0.8247)	(0.0007)	(0.1435)	(0.2849)
Central Wealth Group Holdings	-0.001	0.0488	0.9543***	-0.017***	0.0237	0.9949***	0.1077***	0.2821***
	(0.0011)	(0.0484)	(0.1504)	(0.0039)	(0.0307)	(0.0004)	(0.0209)	(0.0994)
Summit Properties	0.0001***	0.0514**	0.0149**	-0.3489***	0.0149	0.9616***	0.2697***	0.858**
	(0)	(0.0222)	(0.0069)	(0.0301)	(0.0361)	(0.0005)	(0.0612)	(0.4235)
ZTR Acquisition	-0.0016**	-0.0801**	0.0961	-2.6756***	-0.0581	0.6238***	0.2742***	1.9461***
	(0.0007)	(0.0392)	(0.2224)	(0.8402)	(0.0675)	(0.1121)	(0.064)	(0.4198)

Note: This table presents the estimation results of the mean and conditional variance equations; i.e., $r_t = a_0 + b_1 r_{t-1} + b_2 Dom.Ind_t + \varepsilon_t$; and $ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ respectively. r_{t-1} represents the lagged value of the observed company returns. $Dom.Ind_t$ is the returns of the benchmark index where the stock is traded. The term h_t is the conditional volatility estimated by the EGARCH process and D_t is a dummy term to provide a coe□cient relating to the observed changes in the conditional volatility in the subsequent 5 days (1 week) following each event for each of our investigated companies. Only the results for the companies with a significant positive D_t term is presented. The values in the parentheses are standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 11: Regression results for significant increases in conditional volatility in the long-run (all days) after their name changes

Company	a_0	r_{t-1}	$Dom.Ind_t$	ω	α	β	γ	D_t
Panel A: Crypto firms								
Hive Blockchain Tech	0.0012***	0.0779	1.4615***	-0.5621***	0.1567***	0.938***	-0.1921***	0.134***
	(0.0002)	(0.1039)	(0.4747)	(0.0061)	(0.0176)	(0.1861)	(0.032)	(0.0164)
Online Blockchain PLC	0	-0.3141**	0	-2.9751**	-0.029	0.6453***	0.9145***	0.7942*
	(0)	(0.1565)	(0)	(1.3374)	(0.1401)	(0.1329)	(0.15)	(0.4774)
Nodechain Inc	0	0.987***	0	-9.999***	0.9451	0.7712***	2.0299	10.825**
	(0)	(0.1574)	(0)	(3.4942)	(4.195)	(0.0539)	(6.8865)	(5.1702)
Blockchain Worldwide	0	-0.048	-0.018	-10**	-0.04	0.026	0.1354	3.3451**
	(0.0027)	(0.0685)	(0.9322)	(4.0706)	(0.1301)	(0.3909)	(0.2648)	(1.4684)
Litelink Technologies	0.0006***	-0.1007***	-0.3735***	-0.1433***	0.1902***	0.986***	-0.1039***	0.0347***
	(0)	(0.0008)	(0.0451)	(0)	(0.0001)	(0.0062)	(0)	(0.0001)
Fortress Blockchain	0	0.2694**	0*	-3.3376***	-0.0087***	0.9173***	0.0119***	2.6545***
	(0)	(0.1081)	(0)	(0.0256)	(0.0004)	(0.0001)	(0.0002)	(0.0395)
Cascadia Blockchain	0.0006***	-0.0134***	-0.5557***	0.1466***	-0.061	0.9971***	0.312***	0.0614**
	(0.0002)	(0.0014)	(0.0962)	(0.0509)	(0.0931)	(0.0003)	(0.0895)	(0.0256)
Blockchain Infrastructure Group AG	0.0004***	0.0381***	-0.0465***	-1.8069***	0.73***	0.8508***	-0.164***	0.2723***
	(0)	(0.0005)	(0.0004)	(0.0276)	(0.0047)	(0.0434)	(0.0027)	(0.0031)
Panel B: Stock firms								
HI Special Purpose Acquisition	0	-0.1337***	0.083*	-1.1734***	0.0968**	0.8955***	0.1907***	0.3856***
	(0.0001)	(0.0273)	(0.0487)	(0.1359)	(0.0443)	(0.012)	(0.073)	(0.0691)
ZTR Acquisition	-0.0016***	-0.0837***	0.1032	-2.7529***	-0.058	0.613***	0.2728***	1.434***
	(0.0005)	(0.0291)	(0.2222)	(0.8123)	(0.0687)	(0.1083)	(0.0642)	(0.3674)

Note: This table presents the estimation results of the mean and conditional variance equations; i.e., $r_t = a_0 + b_1 r_{t-1} + b_2 Dom.Ind_t + \varepsilon_t$; and $ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$, respectively. r_{t-1} represents the lagged value of the observed company returns. $Dom.Ind_t$ is the returns of the benchmark index where the stock is traded and is included in the mean equation to control for the cryptocurrency markets' overall movements. The term h_t is the conditional volatility estimated by the EGARCH process and D_t is a dummy term to provide a coe□cient relating to the observed changes in the conditional volatility in the subsequent "all days" in the sample period following each event for each of our investigated companies. Only the results for the companies with a significant positive D_t term is presented. The values in the parentheses are standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 12: Regression results for the number (percentage) of companies experiencing an increase in their stock returns' conditional variances from short to long-run after their name changes

Panel A: Positive dummy coefficient							
Business area	D^{1d}	D_t^{5d}	D_t^{10d}	D_t^{20d}	D_t^{40d}	D_t^{60d}	D_t^{All}
Crypto	21 (67.74)	21 (67.74)	20 (64.52)	18 (58.06)	18 (58.06)	15 (48.39)	18 (58.06)
Stock	23 (45.1)	23 (45.1)	21 (41.18)	19 (37.25)	21 (41.18)	18 (35.29)	21 (41.18)

Panel B: Significant positive dummy coefficient							
Business area	D^{1d}	D_t^{5d}	D_t^{10d}	D_t^{20d}	D_t^{40d}	D_t^{60d}	D_t^{All}
Crypto	9 (29.03)	9 (29.03)	4 (12.9)	6 (19.35)	7 (22.58)	4 (12.9)	8 (25.81)
Stock	8 (15.69)	11 (21.57)	5 (9.8)	9 (17.65)	8 (15.69)	5 (9.8)	2 (3.92)

Note: This table presents the overall results from the mean and conditional variance equations; i.e., $r_t = a_0 + b_1 r_{t-1} + b_2 Dom.Ind_t + \varepsilon_t$; and $ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta\ln(h_{t-1}^2) + D_t$ respectively. Values in this table show the number of companies that experience an increase in their stock returns' conditional volatility after their name changes. The column headers show the number of days that we analyse the volatility increase after the name changes. The values in the parentheses are the percentage of companies within the sub-groups experiencing an increase in their stock returns' conditional volatility. Panel A (Panel B) reports the number of companies that experience a (significantly) higher conditional volatility in their stock returns.

Table 13: Cross-company net average changes in price discovery measures between name changing companies & stock markets and name changing companies & cryptocurrency markets

Stock Markets	ΔIS	$\Delta IS-r$	ΔCS	ΔILS
Blockchain/Crypto Name Change	-0.0145	-0.0337	-0.0282	+0.0007
Standard Name Change	+0.0184	+0.008	+0.0479	+0.0127

Cryptocurrency Markets	ΔIS	$\Delta IS-r$	ΔCS	ΔILS
Blockchain/Crypto Name Change	+0.02017	+0.0388	+0.0955	+0.1450
Standard Name Change	-0.0155	-0.0227	-0.0274	-0.0082

Note: Cross-sectional average price discovery change based on the type of company investigated is presented above where IS represents the information share, IS-r represents the reverse information share criterion, CS represents the component share of information while ILS represent the information leadership share of information. Upper (lower) panel shows the net price discovery share between name changing companies and the benchmark index of the stock market that they are traded (cryptocurrency markets).