Received: 27 August 2020 | Revised: 18 January 2021 | Accepted: 24 January 2021

DOI: 10.1002/mde.3307

RESEARCH ARTICLE

WILEY

Game of names: Blockchain premium in corporate names

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We examine stock price response around cryptocurrency-related corporate name change announcements using an event study framework. We find that cryptocurrency-related name changes generate larger gains in share price and volume than other corporate name changes. The valuation gains associated with cryptocurrency-related name changes cannot be explained by standard asset pricing factors, firm and stock characteristics, industry specific shocks, or by the presence of outliers. These gains are higher when the announcements happen during periods of high sentiment for cryptocurrencies. There is evidence that shareholders with better access to private information about such name changes are able to front-run other shareholders.

1 | INTRODUCTION

Blockchain is a decentralized digital ledger that facilitates peer-to-peer economic transactions without the need for a trusted third party. The blockchain technology underpins most cryptocurrencies such as Bitcoin and Ethereum, with potential applications in a variety of business contexts, such as managing supply chains (Kamble et al., 2020; Tönnissen & Teuteberg, 2020), improving transparency in the insurance industry (Disparte, 2017), managing employee benefits (Ying et al., 2018), and settlement of financial transactions (Canaday, 2017; Guo & Liang, 2016). However, despite the attention and rich discussions around the blockchain technology in academic research and popular press, in most cases, the purported applications of blockchain technology remain conceptual expositions. There is little empirical evidence regarding the economic value generated by businesses by using these purported applications of the blockchain technology. Nonetheless, the transformative potential of blockchains has evoked considerable interest from the investor community. Some publicly listed firms have devised a simple strategy to exploit the investor's interest around cryptocurrencies and blockchain technology—changing their corporate names to include cryptocurrency-related buzzwords such as “bitcoin” or “blockchain.” Quite often, these name changes are symbolic without any material changes to the underlying business but are nonetheless followed by spectacular gains in their stock prices (Jain & Jain, 2019).

Articles in popular press and anecdotal evidence regarding misleading corporate name changes and the subsequent stock price behavior have engendered some scrutiny from the security market regulators. The U.S. Securities and Exchange Commission (SEC) launched a formal investigation against both Long Blockchain Corp and Riot Blockchain. On January 22, 2018, the U.S. SEC chairman, Mr. Jay Clayton, warned companies against changing their corporate names to imply any association with blockchains without providing adequate disclosures to investors about the nature of business changes and the risks involved. Invoking the Investment Company Act of 1940, which prohibits the use of “materially deceptive or misleading” names, the SEC forced two exchange-traded funds—Reality Shares and Amplify—to drop the word “blockchain” from their fund description.

In the absence of a robust regulatory framework prohibiting such name changes, and with no classification for cryptocurrency firms in traditional industry classification schemes such as Standard Industrial Classification (SIC), this game of name change has become common and surprisingly effective in generating valuation gains. For example, the stock price of Long Island Iced Tea, a beverage company, increased by over 500% following the announcement that it will change its corporate name to Long Blockchain. Bioptix, a medical equipment manufacturing company, experienced a doubling of its stock price within a week of announcing a name change to Riot Blockchain. This practice is reminiscent of the dotcom bubble of the late 1990s. Cooper et al. (2001) found that firms that included some internet-related buzzwords such as “.com,” “.net,” or “internet” in their corporate names during the dotcom bubble earned cumulative average abnormal returns (CAAR) of 74% for the 10 days surrounding the name change announcement.

By employing a standard event study methodology, our study explores the investor behavior around cryptocurrency-related name change announcements and attempts to answer the following questions: Are cryptocurrency-related name changes associated with valuation gains? If there are valuation gains, are they transient or permanent? Can standard asset pricing factors explain such valuation gains around name change announcements? Which group of shareholders benefits the most from these valuation gains? The study finds a significant increase in both stock return and trading volume around the cryptocurrency-related name change announcements. The abnormal returns and abnormal volume accompanying cryptocurrency-related name changes are larger than those experienced around other name change announcements, which are unrelated to cryptocurrencies. This surge in price and trading volume is robust to deletion of outliers and cannot be explained by standard asset pricing factors or any industry-specific shock. Only investor sentiment for cryptocurrencies and the momentum of "bitcoin" returns are positively related to such valuation gains. Nevertheless, these gains are transient and not persistent. Identifying the date of name change announcement as the event day or Day 0, we find evidence of postannouncement negative drift in cumulative abnormal returns (CAR) as early as Day +6 (6 days after the event), and the stocks give up almost all abnormal valuation gains around Day +29. Further, using Thomson ONE Banker's investor classification, we divide the significant shareholders of a firm into two groups, namely, strategic entities and investment managers.[1] We find that strategic entities are able to derive the greater benefit from this short-term valuation gains accompanying cryptocurrency-related name change announcement. Thus, our results are consistent with the insider trading-information leakage hypothesis of Keown and Pinkerton (1981), who documented excess stock returns prior to the first public announcement of planned mergers.

Our study makes several contributions to the existing literature. First, to the best of our knowledge, this is the first study that compares the valuation gains observed around cryptocurrency-related name change with those observed around other corporate name changes. Some earlier studies document abnormal stock price increase around cryptocurrency-related name changes (Jain & Jain, 2019). However, other types of corporate name changes have also been associated with an abnormal increase in stock prices (Horsky & Swyngedouw, 1987; Karim, 2011; Kot, 2011). Thus, it is of interest to examine whether the investor behavior around cryptocurrency-related name changes is different from that observed around other corporate name changes. Second, we extend the analysis of Jain and Jain (2019) in a number of significant ways. The analysis by Jain and Jain (2019) is based on a sample of only 10 firms that included the word "blockchain" in their names, which they identify using web searches. We use the sample of all global equities available on Thomson Reuters Datastream database that have changed their corporate names to include a cryptocurrency-related buzzword, which allows us to identify a more comprehensive sample of 40 firms. In addition, we consider a wider range of expected return models to estimate abnormal returns, which ensures that our estimates abnormal returns cannot be attributed to standard asset pricing factors, industry-specific shocks, or few outlier firms that generate outsized stock returns around their name change announcement. Third, unlike previous works that only focus on stock price response, we also estimate abnormal trading volume around the cryptocurrency-related change announcements. Considering both stock price response and the change in trading volume provides a more complete representation of investor behavior around name change announcements. For example, a persistent increase in trading volume after the name change announcement is indicative of a general increase in investor interest. Fourth, we provide first evidence that shareholders with better access to private information about the business are able to front-run other shareholders by building substantial long positions in the stock in the pre-announcement period.

The remainder of this paper is organized as follows: Section 2 provides a review of the literature on investor behavior around corporate name change announcements; Section 3 develops the hypotheses; Section 4 describes the methodology; Section 5 describes the data used in the study; Section 6 presents the empirical results; and Section 7 provides the concluding remarks.

2 | LITERATURE REVIEW

The organizational identity literature suggests that name changes can be used to resolve any discrepancies between a firm's own identity and its image as perceived by the outsiders (Gioia et al., 2000). Lee (2001) examined the link between corporate name changes and shareholder reaction. He noted that name changes act as a market signaling mechanism by which information about a firm's identity can be passed on to the investors. However, irrespective of the underlying benefits of the name change decision, it also entails considerable tangible costs, such as advertising and publicity expense, and intangible costs of foregoing an established name, which has already earned some reputation and goodwill in customers' mind (Kashmiri & Mahajan, 2015). In general, the larger the firm, the higher the costs associated with its name change.

Past works that measure the association between corporate name changes and shareholder value creation have found mixed results. Morris and Reyes (1992) and DeFanti and Busch (2011) reported a positive association; Karbhari and Sori (2004) and Andrikopoulos et al. (2007) found a negative association; and Bosch and Hirschey (1989) found no association. The divergence between these results can be at least partly explained by the differences in sample and methodology. Karpoff and Rankine (1994) noted that the evidence for valuation effect of corporate name changes tends to be sample-specific, and it is significantly influenced by the presence of outliers. In addition, because the costs associated with a corporate name change are lower for smaller firms, any sample of firms that announced a corporate name change is likely to be biased towards smaller firms. Therefore, conventional estimates of abnormal returns, such as those based on the market model, are likely to be contaminated by the size effect (Banz, 1981). The results are also sensitive to the choice of event window selected around the name change announcement. For example, DeFanti and Busch (2011) documented a positive valuation effect; however, they examined only a 7-day event window around the name change announcement. Bosch and Hirschey (1989) found a statistically significant 1.62% positive abnormal return for a 21-day period around the announcement day, which was followed by a postannouncement negative drift, which largely offsets the valuation gains observed around the announcement.

Nonetheless, there is evidence that name changes engineered to exploit speculative mania around new "glamour" industries can be quite successful in generating valuation gains. Most notably, at the peak of the dotcom bubble, several firms experienced large valuation gains following the announcement of corporate name changes to Internet-related names (Cooper et al., 2001; Lee, 2001). Sobel (1965) documented similar speculative manias in the United States around mining and railroad stocks in the 1850s and around science and technology stocks in the 1960s. If the name changes are indeed associated with valuation gains, shareholders with private information regarding impending name change announcement can front-run other shareholders in building long positions in the stock. If the valuation gains are also transient, this strategy can be classed as a variant of a pump and dump stock price manipulation scheme, wherein a symbolic name change announcement is used to inflate the stock price temporarily. Pump and dump is often characterized by a concomitant short-term spurt in volatility and trading volume, followed by a long-term price reversal (Aggarwal & Wu, 2006; Leuz et al., 2017; Putniņš, 2012). Although any form of pump and dump manipulation is deemed illegal by stock market regulators, pump and dump schemes are pervasive in the unregulated cryptocurrency market (Li et al., 2019). For instance, on January 9, 2018, at the peak of the craze around cryptocurrencies with bitcoin trading near its all-time high, Kodak announced that it would create its own cryptocurrency called KodakCoin. The announcement caused the company's stock to quadruple in 2 days from \$3.10 to \$13.48. On January 8, 2018, 1 day before the announcement, seven members of the nine-member board of directors awarded themselves large stock grants in the form of restricted stock units. The company disclosed this in a set of SEC filings made on January 10, 2018, the day after the KodakCoin announcement. The filings also indicated that some of the restricted stock units had already been exercised. After peaking on January 10, 2018, Kodak's stock price swiftly and steadily declined, and by May 31, 2018, it had given all the gains in share price experienced due to the hype around KodakCoin. The initial coin offering of KodakCoin was scheduled on January 31, 2018, but it was indefinitely delayed after facing regulatory scrutiny from the SEC.

3 | BACKGROUND AND HYPOTHESES

Despite the tremendous costs involved in a corporate name change, many businesses change their names to signal a new strategic direction to its customers, investors, and competitors (Koku, 1997). As a corporate name change is an expensive and unambiguous signal about the new way of doing business, it is an effective tool to exploit speculative mania among investors around the "glamour" industries. We posit that due to the general perception regarding the enormous growth potential of the blockchains and cryptocurrencies, cryptocurrency-related name changes should be associated with an increase in investor interest. Therefore, we propose the following hypotheses:

H1a. Cryptocurrency-related corporate name changes generate positive and significant abnormal returns.

H1b. The valuation gains experienced around cryptocurrency-related name changes are larger than those experienced around name changes that are unrelated to cryptocurrencies.

A complementary indicator of an increase in investor interest is a significant and persistent increase in trading volume. Unlike estimates of abnormal returns that are sensitive to the choice of the expected return model, the abnormal trading volume estimates are model-free. Additionally, even if the run-up in stock price is transient, the trading volume may remain elevated for long periods representing a persistent increase in stock liquidity. We propose the following hypothesis to examine the effect on cryptocurrency-related name changes on trading volume.

H2a. Cryptocurrency-related corporate name changes generate positive and significant abnormal trading volume.

H2b. The increase in trading volumes experienced around cryptocurrency-related name changes is larger than those experienced around name changes that are unrelated to cryptocurrencies.

Because the costs involved in a corporate name change are higher for large and well-established businesses, it is likely that any sample of firms that announced a corporate name change is skewed towards smaller firms with relatively illiquid stocks. We examine whether the valuation gains accompanying the cryptocurrency-related name change announcements can be explained by firm characteristics, the bid-ask bounce effect (Conrad & Kaul, 1993), or a failure to account for transaction costs involved in illiquid stocks. In addition, we try to measure the relation between the general sentiment around cryptocurrencies and the magnitude of abnormal returns observed around cryptocurrency-related name changes. This leads us to the following hypotheses:

H3a. The abnormal returns experienced around cryptocurrency-related corporate name changes are not explained by firm characteristics or liquidity of the stock.

H3b. The abnormal returns experienced around cryptocurrency-related corporate name changes are positively associated with contemporaneous sentiment towards cryptocurrencies.

Finally, we examine whether insiders are able to exploit the private information about impending name change by increasing their ownership stakes prior to the public announcement of the corporate name change. In the presence of information asymmetry between different groups of shareholders, that is, if one group of shareholders is likely to have better access to private business information as compared with another group of shareholders, one would expect the former to outperform the latter in exploiting the valuation premiums associated with name change announcements. This leads us to the following hypothesis:

H4. Strategic entities would outperform Investment managers in exploiting the valuation gains associated with cryptocurrency-related name change announcements.

4 | METHODOLOGY

To test the abovementioned hypotheses, we employ a hybrid empirical methodology that rests on the statistical matching methodology on the one hand and the standard event study methodology on the other hand. Both these methods are explained below:

4.1 | Matching

As described earlier, we examine the valuation effect of including a cryptocurrency-related buzzword in the corporate name. To accurately measure this treatment effect, one needs to compare the impact of such name change announcements on the valuation of sample firms and the impact of other corporate name change announcements on the valuation of a different set of firms, that is, control firms. However, greater care should be taken before choosing a comparable set of control firms. For example, if there is a significant difference in market capitalization (ME) between the sample and control firms, it may confound comparison of valuation effects of name change announcements because of the size effect (Banz, 1981), that is, on an average, smaller firms tend to produce larger stock returns than larger firms. Additionally, for tiny firms with thinly traded stocks and little investor interest, any new information can have a large positive effect on their stock prices (Cooper et al., 2001).

Even after controlling for the size of firms, low-priced stocks tend to behave differently than high-priced stocks due to a difference in their investor clientele. Recent research suggests that individual investors prefer low-priced stocks due to their lottery-like characteristics (Bali et al., 2017; Eraker & Ready, 2015; Kumar, 2009). Birru and Wang (2016) show that individual investors suffer from a "nominal price illusion," wherein they overestimate the upside potential of low-priced stocks relative to high-priced stocks. Using a dataset of all stocks traded on U.S. exchanges, Singal and Tayal (2015) found that after controlling for size, high-price stocks outperform low-priced stocks by 4.32% a year over the period from December 1962 to December 2013.

To mitigate these potential confounding factors, we match each sample firm with a control group firm based on ME, price, and the number of shares traded, in order to minimize the difference between the two groups. We use two matching methods—propensity score matching (PSM) and Mahalanobis distance matching (MDM)—to identify the matched control group. In addition to the comparison of the mean values of each characteristic, Ho et al. (2007) and Imai et al. (2008) recommend a comparison of higher moments of the distribution of characteristic to obtain a broader characterization of distributional similarity between the sample firms and the matched control firms. For each characteristic, we compute the variance ratio as the ratio of the variance of the sample group to the variance of the control group. Variance ratios close to 1 are indicative of a good balance between the sample firms and control firms. Once the matched control group is finalized, we perform an event study to explore the impact of corporate name change announcements on both sample and control group of firms.

4.2 | Event study

The date of the name change announcement is considered Day 0, and it is referred hereafter as the event date. The event window notation $[-x, +y]$ corresponds to an $(x + y + 1)$—day period, from x trading days before the event date to y trading days after the event date. The daily abnormal return for stock k is calculated as the difference stock return on day t, $R_{k,t}$, and the expected stock return on day t, $E(R_{k,t})$, estimated using a particular expected returns model.

$$AR_{k,t} = R_{k,t} - E(R_{k,t})$$

The cumulative average abnormal return over the event window $[p, q]$ is estimated as follows:

$$CAAR_{pq} = \sum_{t=p}^{q} \sum_{k=1}^{N} AR_{k,t},$$

where N is the total number of firms and $\sum_{k=1}^{N} AR_{k,t}$ is the average abnormal return on day t.

To ensure that our CAAR estimates are not sensitive to the specification of the expected return model, we estimate abnormal returns using four expected return models, namely, the market model, the market model with GARCH errors, the Fama–French 3-factor model, and the Carhart 4-factor model. Using multiple expected returns models gives us some confidence that our CAAR estimates are not an artifact standard asset pricing anomalies (Fama & French, 1996). For example, the CAAR estimated using the Carhart 4-factor model cannot be explained by traditional asset pricing factors such as market excess returns, size, book-to-market ratio, and momentum.

5 | DATA

Isolating the valuation effect of cryptocurrency-related name changes is difficult as corporate name changes are usually associated with abnormal stock price behavior. For example, Bosch and

Hirschey (1989) and Kot (2011) observe a positive stock price reaction to name changes announced due to a business restructuring or a merger or acquisition. However, they document a postannouncement negative drift that largely canceled these valuation gains over the long run. Because our primary objective is to measure the valuation effect of including a cryptocurrency-related buzzword in the corporate name, we exercise some precautions to avoid potential confounding factors that may explain our results.

We identify all publicly listed firms in the Datastream database that changed their corporate name at least once during the period from January 2009 to May 2019 and whose latest corporate name includes one or more cryptocurrency-related buzzwords. We consider three cryptocurrency-related buzzwords, namely, “blockchain,” “bitcoin,” or “crypto,” which allow us to identify corporate names signaling some association with cryptocurrencies. This provides us with an initial sample of 110 firms. Next, we exclude 56 firms from our sample that already had a cryptocurrency-related buzzword in their previous corporate name. This ensures that the corporate name change announcement signals new information to the market participants regarding the firm's association with cryptocurrencies. Finally, we exclude those firms from our sample that had any contaminating events within the longest event window used in our analysis, 30 days before the name change announcement to 50 days after the name change announcement. We consider fresh equity offering, merger, acquisition, spin-off, and going private before the name change as contaminating events. This removes an additional 14 firms, and the remaining 40 firms are used as the sample firms in this analysis. Table A1 describes the step-by-step process used to generate the sample of firms that have changed their corporate names to include cryptocurrency-related buzzwords during the period from January 2009 to May 2019.

Because most corporate name changes are associated with abnormal stock returns, we contrast the valuation effect of cryptocurrency-related name change announcements with that of other corporate name change announcements. For this comparison, we identify a control group of 11,949 firms that announced corporate name changes during the sample period and where the new corporate name was unrelated to cryptocurrencies. Panel A of Table A2 compares the sample firms and the control group firms based on three basic characteristics: ME, Price, and Shares traded. ME is the average of daily ME (dollar-denominated), Price is the average of daily closing price (unadjusted and dollar-denominated), and Shares traded is the average daily number of shares traded. All characteristics are calculated using daily data in the pre-event window [−180, −30]. We find that as compared with the control group firms, the sample firms tend to be considerably smaller with lower-priced and less frequently traded stocks. The average daily ME is \$80.95 million for the sample firms and \$1033.71 million for the control firms. The average daily stock price is \$1.16 for the sample firms and \$48.59 for the control firms.

Panels B and C of Table A2 show the difference between the characteristics of sample firms and matched control firms after PSM and MDM, respectively. Both matching methods reduce the difference between the characteristics of sample firms and control firms considerably. For example, before matching, the average ME is \$80.95 million for sample firms and \$1033.71 million for the control group firms. After PSM (MDM), the average ME of the matched control firms is \$96.86 (\$81.2) million. MDM identifies a better-matched control group than the PSM with a balance improvement of over 99% overall characteristics.

Both PSM and MDM improve the balance in terms of variance ratios. In particular, MDM leads to variance ratios that are very close to 1 for all three characteristics. For each characteristic, the Kolmogorov–Smirnov statistic measures the maximum distance between the empirical cumulative distribution functions between the two groups, with a value of 0 indicating identical distributions and a value of 1 indicating that there is no overlap between the two distributions. MDM performs better than PSM with smaller Kolmogorov–Smirnov statistic values for all three characteristics. For the subsequent analysis, we use the matched control firms identified using MDM as the matched control group. However, the results remain qualitatively similar to the matched control group identified using PSM.

To ensure that the impact of cryptocurrency-related name change is free from any bias induced by extreme observations, we also compute CAAR of the outlier-adjusted sample firms. The outlier-adjusted sample comprises all sample firms except those that fall in the top 10% or bottom 10% in terms of the cumulative abnormal return generated over the period from Day −30 to Day 50.

Hence, we estimate CAAR for three sets of firms: sample firms, outlier-adjusted sample firms, and matched control firms using four expected return models as stated earlier. Among them, the Fama–French 3-factor model and the Carhart 4-factor model require additional data of three Fama–French factors and the Momentum factor, which are obtained from Kenneth French's data library at daily interval.

6 | EMPIRICAL ANALYSIS

6.1 | Descriptive statistics

Table A3 reports some descriptive statistics for sample firms and matched control firms around the date of the name change announcement. Considering the event day as Day 0, the pre-event period refers to the period from Day −30 to Day −1, and the post-event period refers to the period from Day +1 to Day +30. Unadjusted price (\$) is the daily average of unadjusted dollar-denominated closing price. Return (%) and std. dev. of return (%) denote the average daily return and its standard deviation. The table further reports the logarithmic value of average daily volume of trades along with their standard deviation and the logarithmic value of average daily ME for all sample and matched control firms. All statistics are calculated using daily data.

The average price of both sample and matched control firms increases on the event day as compared with the average price in the pre-event period. However, sample firms experience a much higher increase in price than the matched control firms. The average price for sample (matched control) firms increases by 43.1% (10.78%), from an average price of \$1.48 (\$1.002) in the pre-event period to \$2.119 (\$1.11) at the end of Day 0. The sample firms also experience a greater increase in return, volume, and ME on the event day as compared with the matched control firms. A similar pattern is followed in the post-event period. In the post-event period, the sample firms continue to experience a greater increase in trading price, return, volume, and ME as compared with matched control firms.

The result suggests that, in general, corporate name change announcements have a positive effect on share prices and investor interest reflected by greater trading volume. This increase in share price and volume persists for at least some time after the event day. On an average, cryptocurrency-related name changes generate larger gains in share price and volume than other corporate name changes.

6.2 | Do cryptocurrency-related name change announcements generate valuation gains?

Table A4 reports the CAAR generated over different event windows for all three set of firms. We find that both sample and matched control firms experience positive and significant valuation gains close to the name change announcement date. However, these valuation gains for sample firms are larger and more persistent than those of matched control firms. To measure these differences statistically, we have performed a Welch *t* test. Using the Carhart 4-factor model, we estimate that the sample (control) firms generate 14.2% (13.6%) CAAR for the event window [−1, +1]. This difference in valuation gains between these two sets of firms is statistically insignificant (Welch *t* stat = 1.051). This evinces that the sample firms are not unique in generating abnormal positive returns close to the name change announcement. However, further investigation reveals that for the control group firms, most of the valuation gains are concentrated only within the event window [0, +1]. Beyond that, such valuation gains do not exist for control firms. In contrast, the sample firms continue to generate positive abnormal returns for several days surrounding the event day. For example, sample (control) firms generate a CAAR of 23.3% (14.5%), 32.2% (15.9%), and 28.0% (13.4%) in 7, 9, and 11 trading days surrounding the event date, respectively. The Welch *t* statistics computed for these three windows are 1.969, 1.853, and 1.764. These significant differences in valuation gains suggest that the impact of name change announcements is more prominent for sample firms compared with that of matched control firms. Figure B1a,b, which plots CAAR estimates and corresponding *t* statistics obtained from the Carhart 4-factor model for the various event windows, further corroborates our findings. It is evident from the plots that the impact of name change announcements of control firms is only significant on event date. However, for the sample firms, the impact is much higher and lasting. Irrespective of the choice of the expected returns model, CAAR generated in the event window [−5, +5] by the sample firms is almost twice that of the control firms. Although the estimated CAAR is positive and significant for both sample and control firms over the event window [−5, +5]—approximately 2 weeks around the name change announcement—we find no evidence of long-term persistence of these valuation gains for either the sample firms or the control firms.

Over the longest event window, [−30, 50]—approximately 10 weeks around the name change announcement—the CAAR generated by both sample firms and control firms is positive but statistically indistinguishable from zero. During these 10 weeks, sample firms generate CAAR of 5.1% (*t* statistic = 0.176), and control firms generate CAAR of 7.2% (*t* statistic = 0.530). Interestingly, the long-term estimates of CAAR are highly sensitive to the choice of expected returns model. For example, the CAAR estimated over these 10 weeks is 43.5% (*t* statistic = 1.826) for the sample firms when abnormal returns are measured using the market model. This finding suggests that the sample firms did generate large stock returns over a longer window. However, most of these returns can be explained by the standard asset pricing factors. Using expected returns specifications that ignore these asset pricing factors, such as the market model, may lead to misleading estimates of valuation gains generated over a long horizon. Kothari and Warner (2004) note that it is important to use size, book-to-market, and momentum factors to measure the abnormal returns, irrespective of whether these factors indicate inefficiency or serve as a proxy for risk. Our findings support their recommendation and suggest that using the market model to measure abnormal returns can be particularly problematic for long-horizon event studies.

The outlier-adjusted sample produces a similar pattern of CAAR as that of the sample firms. Immediately following the name change announcement, the outlier-adjusted sample produces positive and significant valuation gains, whereas, over the long run, these gains are statistically indistinguishable from zero. Thus, there is evidence of short-term valuation gains around cryptocurrency-related name change announcements even when we remove the more extreme observations.

A plausible explanation for observing positive and significant CAAR could be industry-specific shocks, such as a regulatory change or a shift in investor sentiment around cryptocurrencies. For example, 19 of the 40 cryptocurrency-related name change announcements for the sample firms were clustered over the period from October 2017 to February 2018, close to the all-time high price of bitcoin \$19,783 achieved on December 17, 2017. It may, therefore, be argued that the observed valuation gains for the sample firms may be due to a prevailing favorable investor sentiment during this period,and not due to the name change announcement. To remove the effect of the factors that influence the cryptocurrency industry, we estimate CAAR for our sample firms using the industry-adjusted market model similar to the one used by McGuire and Dilts (2008). For the industry-adjusted market model, abnormal returns are estimated using a market model where the market factor is substituted by a cryptocurrency industry index. The cryptocurrency industry index is calculated as a value-weighted index of 56 cryptocurrency firms that did not change their names during the sample period. Because cryptocurrency firms are not classified under the standard industry classification schemes such as the SIC or the Global Industry Classifications Standard (GICS), we use Worldscope's extended business descriptions to identify these firms.

Using the industry-adjusted market model can be problematic if the sample firms are considerably different from the firms that comprise the cryptocurrency industry index. For example, if sample firms have much smaller ME than the constituent firms of the cryptocurrency industry index, the estimated abnormal returns could be an artifact of the "size effect." To test whether the sample firms have significantly different characteristics than the firms that comprise the cryptocurrency industry index, we estimate a logistic regression to model the likelihood of name change among the set of all cryptocurrency firms. We use a combined sample of 40 sample firms that changed their names and 56 cryptocurrency firms that did not change their names during the sample period. The dependent variable is an indicator variable, which equals 1 if the firm changed its name during the sample period and 0 otherwise. The following firm characteristics are used as explanatory variables. lnME is the logarithm of the average daily ME (dollar-denominated). lnPrice is the logarithm of the average of daily closing price (unadjusted, dollar-denominated). lnVolume is the logarithm of the average of daily number of shares traded. Volatility is the standard deviation of daily returns. Profitability is the average return on invested capital, Leverage is the average of the ratio of the book value of total debt to book value of common equity, and Tangibility is the average of the ratio of net tangible assets to total assets. The exponentiated coefficients (odds ratios) for the logistic regression are reported in Table A5. The results suggest that the sample firms are comparable with the firms that comprise the cryptocurrency industry index in terms of all firm characteristics, with the exception of lnVolume, which is lower for the sample firms.

The last row of Table A4 reports the CAAR estimated using the industry-adjusted market model. We find that the sample firms comfortably outperform the value-weighted cryptocurrency index, producing an industry-adjusted CAAR of 17.3% (t statistic = 2.111) and 21.8% (t statistic = 2.074) over the event windows [0, +1] and [−5, +5], respectively. The results suggest that the short-term valuation gains experienced by sample firms cannot be attributed to some latent industry-wide phenomena.

From Figure B1a,b, we find no evidence of significant abnormal return generated prior to name change announcement day. Over the 30-day period from Day −30 to Day −1, the estimated CAAR is 12.57% (t statistic = 1.079) for sample firms and −6.59% (t statistic = −0.751) for control firms. Immediately following the announcement, both sets of firms experience sharp valuation gains. However, the sample firms experience larger valuation gains than the matched control firms. Most of the valuation gain for the matched control firms occurs on the event day, and their CAAR plot flattens after Day 0. In contrast, the sample firms continue to experience valuation gains until 6 days after the event day. Over the event window [0, 6], sample firms and matched control firms generate a CAAR of 29.27% (t statistic = 2.918) and 14.56% (t statistic = 1.807), respectively. After Day 6, the sample firms experience a postannouncement negative drift that largely offsets these short-term valuation gains. The results support hypotheses H1a and H2a, insofar as cryptocurrency-related name changes generate much larger valuation gains than other corporate name changes. Nonetheless, these valuation gains are transient, and they dissipate almost entirely by Day 29 (refer Figure B1a).

6.3 | Robustness test

Apart from computing abnormal returns for outlier-adjusted sample firms and sample firms using the industry-adjusted market model, we have employed additional robustness tests to investigate the impact of including a cryptocurrency-related buzzword in the corporate name.

6.3.1 | Effect of cryptocurrency-related name change announcements on trading volume

For each firm k, we define relative volume on trading day t as the ratio of the number of shares traded on that day (n_{kt}) to the total number of shares outstanding (S_{kt}). The raw measures of daily trading volume, such as relative volume, usually display a significant positive skew. However, a log transformation yields trading volume measures that are approximately normally distributed (see, for example, Ajinkya & Jain, 1989; Cready & Ramanan, 1991). We estimate a daily measure of log-transformed relative volume, V_{kt} (hereafter referred to as volume for brevity), as follows:

$$V_{kt} = \log\left(\frac{n_{kt}}{S_{kt}}\right).$$

We use the mean-adjusted daily volume as the measure of abnormal volume, AV_{kt}.

$$AV_{kt} = V_{kt} - \bar{V}_k,$$

where $\bar{V}_k$ is the mean trading volume, calculated as the daily average of trading volume V_{kt} estimated over the pre-event window [−180, −31] (hereafter referred to as the pre-event period).

The cumulative average abnormal volume (CAAV) over the event window [t_1, t_2] is estimated as follows:

$$CAAV_{pq} = \sum_{t=t_1}^{t_2}\sum_{k=1}^{N} AV_{kt},$$

where N is the total number of firms and $\sum_{k=1}^{N} AV_{kt}$ is the AAV on day t.

Table A6 reports the CAAV over the event windows considered in Table A4. For all three sets of firms, and across all event windows, the estimated CAAV is positive and significant. Thus, in general, the trading volume on days around the name change announcement exceeds the daily average of trading volume during the pre-event period. However, the CAAV estimates for sample firms are considerably larger than those obtained for the matched control firms, indicating that the increase in trading volume around cryptocurrency-related name change announcements is particularly large. Across all event windows, the CAAV estimates for the sample firms are always close to or more than four standard errors from 0, whereas for the matched control firms, they are about two standard errors from 0.

Over a period from Day 0 to Day +1, we estimate a CAAV of 4.018 (t statistic = 4.923) for the sample firms and a CAAV of 1.857 (t statistic = 1.954) for the matched control firms. This suggests that during this 2-day period, the daily relative volume of sample firms (matched control firms) is 7.46 (2.53) times of that observed during the pre-event period. For the longest event window [−30, 50], we estimate a CAAV of 100.899 (t statistic = 4.684) for the sample firms and a CAAV of 58.530 (t statistic = 2.133) for the matched control firms. This suggests that during this 81-day period, the daily relative volume of sample firms (matched control firms) is 3.47 (2.05) times that observed during the pre-event period.

Figure B2a plots the daily AAV estimates for all three sets of firms, and Figure B2b plots the corresponding t-statistics for these AAV estimates. We find that sample firms begin to experience positive and significant abnormal trading volume much earlier than the matched control firms. For example, approximately 5 weeks before the name change announcement, on Day −25, we estimate an AAV of 1.302 (t statistic = 3.529) for sample firms and an AAV of 0.512 (t statistic = 1.295). Over the 30-day period from Day −30 to Day −1, none of the 30 AAV estimates for matched control firms are more than two standard errors from 0, whereas 21 out of 30 AAV estimates for sample firms are more than two standard errors from 0.

Both sample firms and matched control firms witness an increase in trading volume on the event day. However, we find that the trading volume for sample firms increases much more sharply than that of the matched control firms. We estimate an AAV of 2.066 (t statistic = 4.751) for sample firms and an AAV of 1.12 (t statistic = 2.334) for matched control firms on Day 0. The relative volume of sample firms (matched control firms) on the event day is 7.89 (3.06) times that observed during the pre-event period. These findings are consistent with the hypotheses H2a and H2b. Moreover, this increase in trading volume is persistent, and it is robust to the exclusion of outliers from the set of sample firms. For all three sets of firms, we find the AAV estimates remain positive and significant even 10 weeks after the event day. Thus, there is evidence of a large and stable increase in investor interest after the name change announcement.

6.3.2 | Can bid-ask bounce or the prevailing sentiment towards cryptocurrencies explain the abnormal returns?

The large valuation gains observed around name change announcements could be due to an upward bias in measuring abnormal returns. This upward bias may be caused by the bid-ask bounce effect (Conrad & Kaul, 1993) or by a failure to account for substantial transaction costs emanating from wide bid-ask spreads of these relatively illiquid stocks. To examine the relation between bid-ask spread and abnormal returns, we estimate the average relative bid-ask spread for all sample firms. For each day t, the relative bid-ask spread is calculated as $(ask_t - bid_t)/((ask_t + bid_t)/2)$. The average relative bid-ask spread is the average of the daily relative bid-ask spread estimated over the pre-event window [−180, −31]. Then, we estimate the cross-sectional correlation between CAR generated by sample firms and their corresponding relative bid-ask spread. The cumulative abnormal return, $CAR_{k,\ pq}$, for a sample firm k, over the event window $[p,q]$ is estimated as follows:

$$CAR_{k,\ pq} = \sum_{t=p}^{q} AR_{kt}.$$

If the large abnormal returns are caused by upward bias induced by a bid-ask bounce or by the failure to account for transaction costs, one should expect a positive association between CAR and relative bid-ask spread. Table A7 reports the cross-sectional association between CAR and the average relative bid-ask spread for two event windows: [0, +1] and [−30, +50]. For both periods, we find no evidence of a positive and significant cross-sectional association between CAR and the average relative bid-ask spread. Therefore, the observed valuation gains are unlikely to be an artifact of microstructure induced upward bias in the abnormal return estimates. The findings support hypothesis H3a.

The cryptocurrency markets are extremely volatile and prone to speculative bubbles (Cheah & Fry, 2015; Fry & Cheah, 2016), and therefore, the investor sentiment towards cryptocurrencies varies considerably over time. Intuitively, one would expect the observed valuation gains following cryptocurrency-related name change announcements should be positively related to the investor sentiment around cryptocurrencies. Specifically, large valuation gains should be observed in periods in which investors are positive about the prospects of cryptocurrencies. Following Baig et al. (2019), we proxy investor sentiment towards cryptocurrencies using Google Trends data. Weekly interest over time in the search terms "Bitcoin" and "Blockchain" was extracted from Google Trends data for the period from March 1, 2014 to May 31, 2018, which includes all event dates for our sample firms. The search interest over time is represented as a normalized index varying from 0 to 100 with 0 (100) representing the lowest (highest) search interest in the search term over the period from March 1, 2014 to May 31, 2018. We match each firm's event date with the closest weekly value of the Google Trend Index. Then, we define two proxy variables to represent investor sentiment towards cryptocurrencies close to or at the event date, namely, lnBitcoinTrend and lnBlockchainTrend. lnBitcoinTrend and lnBlockchainTrend are the logarithms of the Google Trend Index value for the search term "Bitcoin" and "Blockchain," respectively. Table A7 reports the cross-sectional association between CAR and the cryptocurrency sentiment variables for two event windows: [0, +1] and [−30, +50]. We find that the association between lnBitcoinTrend and the CAR generated by sample firms is positive and significant for both event windows. The association between lnBlockchainTrend and CAR is also positive, although it is weaker in terms of statistical significance. This suggests that the valuation gains tend to be higher when the name change announcements happen during periods of high sentiment for cryptocurrencies. The positive and significant association between CAR and sentiment for cryptocurrencies supports hypothesis H3b.

To estimate or quantify the (treatment) effect of including a cryptocurrency-related buzzword in the corporate name on firms' valuation as accurate as possible, a great care should be taken when defining the determinants of the valuation gains. Because the valuation gains are measured by positive abnormal returns earned by these corporates, we have identified various firm level characteristics and bitcoin momentum that may potentially explain such abnormal gains. Table A8 explores the determinants of these valuation gains by regressing CAR on these explanatory variables. The dependent variable, firm-level CAR, is measured using the Carhart 4-factor model over different event windows surrounding the name change announcement. The explanatory variables are estimated using daily data in the pre-event window [−180, −31]. We use six firm-level characteristics as explanatory variables: lnME is the logarithm of the average of daily ME (dollar-denominated); lnPrice is the logarithm of the average of daily closing price (unadjusted, dollar-denominated); lnSharesTraded is the logarithm of the average of daily number of shares traded; MoM is the annualized daily dollar-denominated return, and StdDev is the standard deviation of these daily returns; and USFirms is an indicator variable equal to one for the U.S. firms and zero for other firms. The indicator variable serves as a proxy to examine whether the prevalence of adding a cryptocurrency-related keyword to corporate names and the subsequent generation of abnormal returns is a function of country-specific regulatory oversight. For instance, the U.S. SEC has repeatedly warned companies with no meaningful track record in pursuing the distributed ledger technology against misleading investors by changing their corporate names to capitalize on the perceived promise of blockchains. In addition, we use the pre-event momentum of bitcoin returns, MoM_{BTC}, as the annualized daily dollar-denominated return of Bitcoin estimated over the pre-event window [−180, −31].

The results suggest that valuation gains generated around name change announcement are largely unrelated to pre-event stock and firm characteristics, and they are not significantly different for the U.S. and the non-U.S. firms. With the exception of StdDev, which displays a weak negative relation with future CAR, none of the other pre-event firm-level variables display a significant relation with future CAR. The regression coefficient for StdDev is negative across all event windows. However, it is statistically significant for only two out of the nine event windows we consider. The most reliable predictor of future CAR in our regressions is MoM_{BTC}, which shows a positive relation with future CAR across all event windows, and the relation is statistically significant for seven out of nine event windows. These results support hypothesis H3b and suggest that valuation gains around name change announcements tend to be larger (smaller) when bitcoin returns displayed high (low) momentum during the pre-event period.

6.4 | Do insiders exploit these valuation gains better than other groups of investors?

The CAAR plot of sample firms (Figure B1a) is reminiscent of a classical pump and dump scheme featuring a dramatic short-term increase in prices till Day +6, followed by a negative drift until almost all of the valuation gains are reversed around Day +29. If cryptocurrency-related name changes are indeed a ploy to capitalize on the sentiment surrounding cryptocurrencies, it is likely that insiders with prior knowledge of the future name change would be able to outperform other groups of investors in exploiting these valuation gains.

We classify the largest shareholders of the sample firms into two groups, namely, investment managers and strategic entities using the Thompson ONE Banker classification. Table A9 examines the changes in the positions of investment managers and strategic entities for our sample firms over different periods surrounding the name change announcement. Panel A reports the mean position change for the investment managers and the strategic entities in six periods: during the two quarters before the event (−Q2 and −Q1), during the second quarter before the event (−Q2), during the first quarter before the event (−Q1), during the first quarter after the event (+Q1), during the second quarter after the event (+Q2), and during the two quarters after the event (+Q1 and +Q2). Panel B lists the results of equality tests within the investor group and between the two investor groups over these periods. Consistent with hypothesis H4, we find that strategic entities increased their holdings substantially more than the investment managers during the preannouncement periods. In the two quarters before the name change announcement, the average position of strategic entities $(\hat{\beta}_1)$ increased by 16.956% (t statistic = 3.048), whereas that of investment managers $(\hat{\alpha}_1)$ increased by 6.074% (t statistic = 1.944), and the difference between the two groups $(\hat{\alpha}_1 - \hat{\beta}_1)$ is statistically significant. Due to a greater increase in positions prior to the name change announcement, the strategic entities stand to gain more than the investment managers from the valuation gains following the name change announcement. The position changes in the postannouncement period are much smaller. In the two quarters after the name change announcement, the mean position change for investment managers is 0.016% (t statistic = 0.068), whereas it is 2.198% (t statistic = 1.715) for the strategic entities. Also, the difference between the two groups $(\hat{\alpha}_6 - \hat{\beta}_6)$ is statistically indistinguishable from zero. This is expected as after the name change announcement, the strategic entities have no informational advantage over other groups of investors.

7 | CONCLUSION

We measure the effect of cryptocurrency-related corporate name changes on shareholder value. Despite being a costly signaling mechanism, corporate name changes that imply some association with blockchains and cryptocurrencies engender significant investor interest. We find that cryptocurrency-related name changes generate large valuation gains. However, these gains are not persistent, and they are almost entirely reversed within 30 days after the announcement. The abnormal returns cannot be explained by standard asset pricing factors, by the firm and stock characteristics, by some industry-specific shock, or by few outlier firms that generate outsized returns around their name change announcement. In contrast, we find that the contemporaneous sentiment around cryptocurrencies has a positive and significant association with abnormal returns. More specifically, the observed valuation gains tend to be higher when the name change announcements happen during periods of high sentiment for cryptocurrencies.

On an average, cryptocurrency-related name changes produce a larger increase in stock price and trading volume than those produced by corporate name changes unrelated to cryptocurrencies. There is some evidence that insiders with private information regarding impending name change announcement can front-run other shareholders in building long positions in the stock. We find that strategic entities outperform investment managers in exploiting the valuation gains associated with cryptocurrency-related name change announcements.

We hope that the findings of this study will be useful for both market participants and regulators. Our results suggest that investors should exercise caution before investing in firms that announce a cryptocurrency-related corporate name change without a meaningful track record in the commercial use of blockchain technology. For example, one of the firms in our sample, Riot Blockchain, has repeatedly changed its name, even when name change has material costs for the business. Equity analysts and investors should critically examine whether such strategic change implied by a name change would indeed result in a material improvement in the firm's business prospects. From the perspective of equity market regulators, our results motivate a need for a formal policy to curb the practice of using deceptive or misleading corporate names. The stock price behavior around cryptocurrency-related name changes is remarkably similar to a pump and dump scheme characterized by a sudden run-up in stock prices due to false and misleading positive information, followed by a reversal as stock prices revert to the original value.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTE

[1] Strategic entities are large shareholders that invest in the firm for strategic interests and controlling purposes. Strategic entities also include insiders such as senior executives and directors of the firm. Investment managers are buy-side institutions such as private equity, hedge funds, pension funds, and banks and trusts that own stakes in a large number of firms for investment purposes.

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How to cite this article: Sharma P, Paul S. Game of names: Blockchain premium in corporate names. *Manage Decis Econ*. 2021;42:1059–1078. https://doi.org/10.1002/mde.3307

APPENDIX A

TABLE A1 Description of the sample

Selection of sample firms:	
Publicly listed firms in Datastream that changed their corporate name at least once during the period from January 2009 to May 2019 and whose latest corporate name includes one or more cryptocurrency-related buzzwords.	110
Deleted firms that already had a cryptocurrency-related buzzword in their previous corporate name.	56
Deleted firms that had any contaminating event(s) within the period from 30 days before the name change announcement to 50 days after the name change announcement	14
Total number of remaining firms	40

Note: This table describes the process used to generate the sample of firms that have changed their corporate names to include cryptocurrency-related buzzwords during the period from January 2009 to May 2019. We consider three cryptocurrency-related buzzwords, namely, "blockchain," "bitcoin," or "crypto." Contaminating events include fresh equity offering, merger, acquisition, spin-off, and going private before the name change announcement.

TABLE A2 Identifying control group using matching

	Sample firms	Control firms	Mean difference	Balance improvement (%)	Variance ratio	Kolmogorov–Smirnov statistic
Panel A: difference between sample and control groups before matching						
ME	80.95	1033.71	−952.76	-	0.00	0.39
Price	1.16	48.59	−47.43	-	0.00	0.23
Shares traded	76182.80	29965.08	46217.71	-	4.86	0.51
Panel B: difference between sample and control groups after propensity score matching						
ME	80.95	96.86	−15.91	98.33	0.8694	0.20
Price	1.16	0.66	0.50	98.94	2.9254	0.30
Shares traded	76182.80	69356.24	6826.55	85.23	0.9744	0.25
Panel C: difference between treatment and control groups after Mahalanobis matching						
ME	80.95	81.20	−0.25	99.97	0.9486	0.10
Price	1.16	1.07	0.09	99.81	0.9629	0.23
Shares traded	76182.80	76194.53	−11.73	99.97	1.0001	0.03

Note: This table describes the balance between sample and control firms based on three characteristics: ME, Price, and Shares traded. ME is the average of daily market capitalization (dollar-denominated), Price is the average of daily closing price (unadjusted, dollar-denominated), and Shares traded is the average of daily number of shares traded. All characteristics are calculated using daily data in the pre-event window [−180, −30]. First two columns report the mean values for these variables for sample firms and control firms, respectively. Mean difference is the difference between Columns 1 and 2. Column 4 reports the percentage improvement in balance after using a matching method to identify a suitable control group for the sample firms. For a particular characteristic, the variance ratio column reports ratio of variance of the sample group to the variance of the control group. For each characteristic, the Kolmogorov–Smirnov statistic measures the difference between the empirical cumulative distribution functions between the two groups, with a value of 0 indicating identical distributions and a value of 1 indicating that there is no overlap between the two distributions. Panel A reports the difference in mean of market ME, Price, and Volume between sample and control firms before any matching has been done. Panels B and C report the percentage improvement in balance between these two groups of firms using propensity score matching and Mahalanobis matching, respectively.

TABLE A3 Descriptive statistics

Characteristics	Set of firms	Pre-event period [−31, −1]	Event day Day 0	Post-event period [+1, +30]
Unadjusted price ($)	Sample	1.483	2.119	4.352
	Matched control	1.002	1.110	1.032
Return (%)	Sample	1.448	3.000	0.981
	Matched control	0.552	1.121	0.020
Std. dev. of return (%)	Sample	2.901	-	4.231
	Matched control	2.667	-	3.263
Log volume	Sample	2.051	3.705	3.406
	Matched control	2.582	2.957	3.198
Std. dev. of volume (%)	Sample	42.060	-	41.552
	Matched control	38.080	-	35.651
Log market capitalization	Sample	12.523	12.589	12.667
	Matched control	11.453	11.456	11.443

Note: This table describes the balance between sample and control firms based on three characteristics: ME, Price, and Shares traded. ME is the average of daily market capitalization (dollar-denominated), Price is the average of daily closing price (unadjusted, dollar-denominated), and Shares traded is the average of daily number of shares traded. All characteristics are calculated using daily data in the pre-event window [−180, −30]. First two columns report the mean values for these variables for sample firms and control firms, respectively. Mean difference is the difference between Columns 1 and 2. Column 4 reports the percentage improvement in balance after using a matching method to identify a suitable control group for the sample firms. For a particular characteristic, the variance ratio column reports ratio of variance of the sample group to the variance of the control group. For each characteristic, the Kolmogorov–Smirnov statistic measures the difference between the empirical cumulative distribution functions between the two groups, with a value of 0 indicating identical distributions and a value of 1 indicating that there is no overlap between the two distributions. Panel A reports the difference in mean of market ME, Price, and Volume between sample and control firms before any matching has been done. Panels B and C report the percentage improvement in balance between these two groups of firms using propensity score matching and Mahalanobis matching, respectively.

TABLE A4 Cumulative average abnormal return

Expected returns model	Set of firms	Event window −1 to +1	−2 to +2	−3 to +3	−4 to +4	−5 to +5	−30 to +50	0 to +1	+1 to +15	+1 to +50
Market model	Sample	0.159** (1.995)	0.181** (2.496)	0.249*** (3.089)	0.312*** (2.977)	0.267** (2.507)	0.435* (1.826)	0.142** (1.983)	0.187* (1.645)	0.104 (0.544)
	Outlier-adjusted	0.172* (1.931)	0.169** (2.025)	0.233*** (2.654)	0.232** (2.412)	0.209** (2.082)	0.414** (2.061)	0.148* (1.812)	0.163 (1.409)	0.078 (0.450)
	Matched control	0.138* (1.655)	0.140* (1.674)	0.145* (1.788)	0.158** (2.090)	0.137* (1.809)	0.076 (0.578)	0.140* (1.727)	0.029 (0.690)	0.071 (1.025)
Market model with GARCH errors	Sample	0.172** (2.016)	0.204*** (2.635)	0.288*** (3.288)	0.361*** (3.272)	0.315*** (2.792)	0.790*** (2.391)	0.154** (2.015)	0.269** (2.214)	0.329 (1.413)
	Outlier-adjusted	0.178* (1.899)	0.178** (2.014)	0.255*** (2.675)	0.256** (2.553)	0.228** (2.166)	0.583* (1.610)	0.150* (1.742)	0.205* (1.645)	0.194 (0.806)
	Matched control	0.141* (1.709)	0.142* (1.771)	0.141* (1.905)	0.151** (2.290)	0.119* (1.898)	−0.090 (−0.742)	0.149* (1.826)	0.006 (0.136)	−0.032 (−0.364)
Fama–French 3-factor model	Sample	0.119 (1.461)	0.178** (2.237)	0.237*** (2.724)	0.313*** (2.626)	0.280** (2.096)	0.264 (1.023)	0.124 (1.630)	0.137 (1.093)	0.007 (0.036)
	Outlier-adjusted	0.171* (1.846)	0.154* (1.726)	0.210** (2.200)	0.196* (1.714)	0.158* (1.887)	0.134 (0.571)	0.146* (1.754)	0.134 (1.027)	0.079 (0.425)
	Matched control	0.137 (1.635)	0.139* (1.663)	0.145* (1.796)	0.158** (2.061)	0.134* (1.757)	0.009 (0.068)	0.138* (1.713)	0.022 (0.535)	−0.006 (−0.079)
Carhart 4-factor model	Sample	0.142* (1.656)	0.169** (2.171)	0.233*** (2.695)	0.322*** (2.618)	0.280** (2.035)	0.051 (0.176)	0.129* (1.702)	0.116 (0.912)	0.154 (0.661)
	Outlier-adjusted	0.170* (1.838)	0.150* (1.692)	0.205** (2.156)	0.188* (1.666)	0.148 (1.211)	0.095 (0.398)	0.148* (1.790)	0.136 (1.073)	0.094 (0.507)
	Matched control	0.136 (1.629)	0.140 (1.641)	0.145* (1.791)	0.159** (2.080)	0.134* (1.777)	0.072 (0.530)	0.137* (1.704)	0.018 (0.426)	0.026 (0.380)
Industry-adjusted market model	Sample	0.212** (2.374)	0.208** (2.460)	0.245*** (2.727)	0.239** (2.339)	0.218** (2.074)	0.509*** (3.004)	0.173** (2.111)	0.198* (1.764)	0.147 (1.002)

Note: This table reports cumulative average abnormal returns (CAAR) for all sample firms that have changed their names by including buzzwords like "blockchain," "bitcoin," or "crypto" in between January 2009 and May 2019. The abnormal returns are calculated for various event windows where the events are the announcement of name change. Each cell reports the CAAR across all firms for the respective event windows. Panel A compares the CAARs of sample firms with outlier-adjusted sample firms (trimmed by 10% on the basis of abnormal returns earned) and price, volume, and market cap matched control firms (matched control group) using four different models: market model, market model with GARCH errors, Fama–French 3-factor model, and Carhart's 4-factor model. Panel B reports industry adjusted CAARs of the sample firms where industry index has been developed using value weighted average return of all cryptocurrency firms. Cross-sectionally adjusted *t* statistics are reported in parentheses.

*Indicates significance at 10% level.

**Indicates significance at 5% level.

***Indicates significance at 1% level.

TABLE A5 Determinants of name change among cryptocurrency firms

	Dependent variable: indicator variable that equals 1 if the firm changed its name during the sample period and 0 otherwise.					
	(1)	(2)	(3)	(4)	(5)	(6)
lnME	0.999 (−0.017)		1.010 (0.193)		0.995 (−0.146)	1.036 (0.629)
BE/ME	1.004 (0.654)		1.003 (0.483)		1.009 (0.806)	1.001 (0.098)
lnPrice		0.972 (−0.934)	0.980 (−0.379)			0.927 (−1.219)
lnVolume		0.950** (−2.067)	0.958 (−1.375)			0.930* (−1.985)
Volatility		1.004 (0.623)	1.004 (0.640)			1.005 (0.703)
Profitability				1.000 (−1.136)	1.000 (−1.084)	1.000 (−0.990)
Leverage				1.000 (−0.623)	1.000 (−0.634)	1.000 (−0.540)
Liquidity				1.000 (1.273)	1.000 (1.211)	1.000 (1.194)
Tangibility				1.000 (−0.158)	1.000 (−0.235)	1.000 (0.315)
Constant	1.498*** (3.700)	1.912*** (4.946)	1.757*** (3.276)	1.454*** (6.020)	1.485*** (2.998)	1.788*** (2.835)
Log Lik	−61.260	−66.295	−59.051	−50.666	−49.799	−46.520
AIC	128.520	140.590	130.102	111.333	113.597	113.039

Note: This table reports the exponentiated coefficients (odds ratios) for a logistic regression that models the likelihood of name change among cryptocurrency firms using a combined sample of 40 sample firms that changed their names and 56 cryptocurrency firms that did not change their names during the sample period. The dependent variable is an indicator variable that equals 1 if the firm changed its name during the sample period and 0 otherwise. All firm-level explanatory variables are estimated using daily data for the full sample period. lnME is the logarithm of the average of daily market capitalization (dollar-denominated). lnPrice is the logarithm of the average of daily closing price (unadjusted, dollar-denominated). lnVolume is the logarithm of the average of daily number of shares traded. Volatility is the standard deviation of daily returns. Profitability is the average return on invested capital, leverage is the average of the ratio of book value of total debt to book value of common equity, tangibility is the average of the ratio of net tangible assets to total assets. This table reports the exponentiated logistic coefficients (odds ratios). *t* statistics are provided in parentheses below the estimated coefficients.

*Indicates significance at 10% level.

**Indicates significance at 5% level.

***Indicates significance at 1% level.

TABLE A6 Cumulative average abnormal volume

	Event window								
Set of firms	−1 to +1	−2 to +2	−3 to +3	−4 to +4	−5 to +5	−30 to +50	0 to +1	+1 to +15	+1 to +50
Sample	6.018*** (5.054)	8.721*** (4.861)	10.980*** (4.407)	13.779*** (4.695)	15.902*** (4.494)	100.899*** (4.684)	4.018*** (4.923)	24.644*** (4.043)	72.692*** (3.918)
Outlier-adjusted sample	5.980*** (4.339)	8.807*** (4.259)	11.032*** (4.065)	13.578*** (4.050)	15.635*** (3.867)	100.956*** (4.064)	4.008*** (4.257)	24.338*** (3.448)	73.705*** (3.429)
Matched control group	2.558** (2.122)	3.435* (1.802)	4.807* (1.838)	6.631** (2.036)	7.725* (1.958)	58.530** (2.133)	1.857* (1.954)	13.593** (2.029)	45.140** (2.241)

Note: This table reports cumulative average abnormal volume (CAAV) for all sample firms that have changed their names by including buzzwords like "blockchain," "bitcoin," or "crypto" in between January 2009 and May 2019. The abnormal volumes are calculated for various event windows where the events are the announcement of name change. Each cell reports the CAAV across all firms for the respective event windows. The table compares the CAAVs of sample firms with outlier-adjusted sample firms and price, volume, and market cap matched control firms (matched control group) using market model (MM). *t* statistics are reported in parentheses.

*Indicates significance at 10% level.

**Indicates significance at 5% level.

***Indicates significance at 1% level.

TABLE A7 Correlation of cumulative abnormal returns with search interest and average relative spread

	Event window for estimating CAR					
	0 to +1			**−30 to +50**		
	Spearman's rho	Kendall's tau	Pearson's correlation	Spearman's rho	Kendall's tau	Pearson's correlation
lnBitcoinTrend	0.365** (2.212)	0.271** (2.326)	0.292* (1.751)	0.327** (1.977)	0.236** (2.024)	0.317* (1.911)
lnBlockchainTrend	0.283* (1.695)	0.195* (1.675)	0.27 (1.616)	0.229 (1.366)	0.19 (1.635)	0.423*** (2.612)
Avg. relative spread	−0.041 (0.184)	0.016 (0.105)	0.223 (1.024)	0.062 (0.282)	0.043 (0.261)	0.043 (0.194)

Note: This table reports the correlation of cumulative abnormal returns (CAR) with search interest and average relative spread. The cumulative abnormal returns (CAR) are measured using Carhart's 4-factor model. Weekly interest over time in the search terms "Bitcoin" and "Blockchain" was extracted from Google Trends data for the period from March 1, 2014 to May 31, 2018, which includes all event dates for our sample firms. The search interest over time is represented as a normalized index varying from 0 to 100 with 0 (100) representing the lowest (highest) search interest in the search term over the period from March 1, 2014 to May 31, 2018. We match each firm's event date with the closest weekly value of the Google Trend Index. lnBitcoinTrend and lnBlockchainTrend are the logarithms of the Google Trend Index value for the search term "Bitcoin" and "Blockchain," respectively. For each day t, the relative bid-ask spread is calculated as $(ask_t - bid_t)/((ask_t + bid_t)/2)$. The average relative spread is the average of the daily relative bid-ask spread estimated over the pre-event window [−180, −31]. t statistics are provided in parenthesis below the estimated correlation coefficients.

*Indicates significance at 10% level.

**Indicates significance at 5% level.

***Indicates significance at 1% level.

TABLE A8 Predictive regressions for cumulative abnormal returns

	Dependent variable: cumulative abnormal returns (CAR)								
	Event window for estimating CAR								
	−1 to +1	−2 to +2	−3 to +3	−4 to +4	−5 to +5	−30 to +50	0 to +1	+1 to +15	+1 to +50
lnME	−0.015 (−0.314)	−0.013 (−0.299)	−0.03 (−0.599)	−0.015 (−0.207)	−0.054 (−0.685)	−0.078 (−0.556)	−0.02 (−0.468)	−0.108 (−1.474)	−0.081 (−0.661)
lnPrice	−0.008 (−0.162)	−0.018 (−0.416)	−0.011 (−0.234)	−0.037 (−0.530)	−0.015 (−0.192)	0.048 (0.349)	0.016 (0.376)	−0.01 (−0.140)	0.061 (0.503)
lnSharesTraded	0.014 (0.162)	−0.048 (−0.592)	−0.089 (−0.987)	−0.119 (−0.926)	−0.221 (−1.560)	0.22 (0.871)	0.046 (0.588)	0.075 (0.561)	0.295 (1.333)
MoM	−0.054 (−1.574)	−0.027 (−0.852)	−0.009 (−0.246)	0.023 (−0.462)	0.007 (−0.132)	−0.157 (−1.584)	−0.049 (−1.599)	−0.046 (−0.884)	−0.105 (−1.212)
StdDev	−0.054 (−0.849)	−0.020 (−0.336)	−0.043 (−0.658)	−0.062 (−0.670)	−0.004 (−0.036)	−0.359* (−1.977)	−0.023 (−0.416)	−0.054 (−0.566)	−0.272* (−1.716)
USFirms	0.287 (1.440)	0.151 (0.817)	0.177 (0.864)	0.217 (0.741)	0.075 (0.233)	0.939 (1.635)	0.078 (0.439)	0.115 (0.380)	0.127 (0.253)
MoM_{BTC}	0.076 (1.577)	0.107** (2.403)	0.118** (2.401)	0.122* (1.732)	0.180** (2.324)	0.314* (2.270)	0.088** (2.068)	0.128* (1.754)	0.126 (1.038)
Constant	0.155 (0.127)	0.675 (0.598)	1.41 (1.130)	1.513 (0.847)	3.018 (1.537)	−1.021 (−0.292)	−0.106 (−0.098)	0.875 (0.475)	−1.522 (−0.497)
R^2	0.293	0.235	0.247	0.187	0.265	0.464	0.267	0.242	0.378
F statistic	1.716	1.276	1.359	0.95	1.491	3.580***	1.507	1.322	2.514**

Note: This table reports the results of predictive regression of cumulative abnormal returns (CAR) on different explanatory variables across various event windows. CARs are measured using the Carhart's four factor model (FF4F). All firm-level explanatory variables are estimated using daily data in the pre-event window [−180, −31]. lnME is the logarithm of the average of daily market capitalization (dollar-denominated). lnPrice is the logarithm of the average of daily closing price (unadjusted, dollar-denominated). lnSharesTraded is the logarithm of the average of daily number of shares traded. MoM is the annualized daily dollar-denominated return, and StdDev is the standard deviation of these daily returns. USFirms is an indicator variable equal to one for the U.S. firms and zero for other firms. MoM_{BTC} is the annualized daily dollar-denominated return of Bitcoin estimated over the pre-event window [−180, −31]. *t* statistics are reported in parenthesis.

*Indicates significance at 10% level.

**Indicates significance at 5% level.

***Indicates significance at 1% level.

TABLE A9 Changes in ownership position for different investors groups

Panel A: mean position change (%)											
Investment managers						Strategic entities					
−Q2 & −Q1	−Q2	−Q1	+Q1	+Q2	+Q1 & +Q2	−Q2 & −Q1	−Q2	−Q1	+Q1	+Q2	+Q1 & +Q2
$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_3$	$\hat{\alpha}_4$	$\hat{\alpha}_5$	$\hat{\alpha}_6$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_6$
6.074*	4.633	1.440	−0.068	0.084	0.016	16.956***	11.692***	5.264**	1.517*	0.681	2.198*
(1.944)	(1.556)	(1.162)	(−0.426)	(0.885)	(0.068)	(3.048)	(3.061)	(2.290)	(2.004)	(1.055)	(1.715)
Panel B: equality tests											
Within investor group						**Between investor groups**					
$\hat{\alpha}_1-\hat{\alpha}_6$	$\hat{\alpha}_2-\hat{\alpha}_5$	$\hat{\alpha}_3-\hat{\alpha}_4$	$\hat{\beta}_1-\hat{\beta}_6$	$\hat{\beta}_2-\hat{\beta}_5$	$\hat{\beta}_3-\hat{\beta}_4$	$\hat{\alpha}_1-\hat{\beta}_1$	$\hat{\alpha}_2-\hat{\beta}_2$	$\hat{\alpha}_3-\hat{\beta}_3$	$\hat{\alpha}_4-\hat{\beta}_4$	$\hat{\alpha}_5-\hat{\beta}_5$	$\hat{\alpha}_6-\hat{\beta}_6$
6.058*	4.550	1.508	14.759**	11.011***	3.748	−10.883*	−7.059	0.000	−1.584**	−0.597	−2.182
(1.933)	(1.527)	(1.207)	(2.586)	(2.843)	(1.548)	(−1.706)	(−1.458)	(1.162)	(−2.049)	(−0.916)	(−1.575)

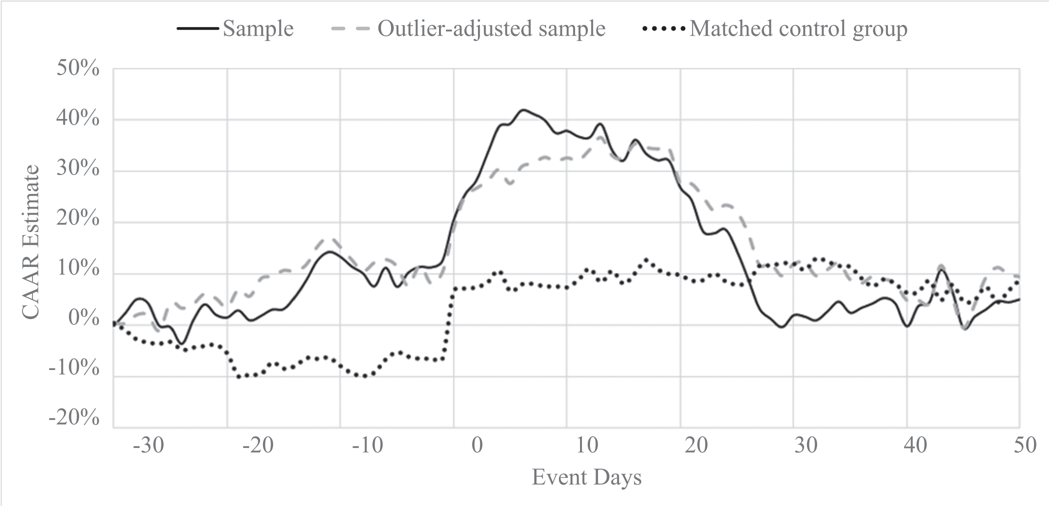
Note: This table reports the changes in the positions of investment managers and strategic entities for the sample firms over different periods surrounding the name change announcement. Investment managers include investment advisors, private equity, hedge funds, pension funds, and banks/trusts. Strategic entities comprise individual investors, corporations, and other insider investors. Panel A reports the mean position change for the investment managers and the strategic entities in six periods: during the two quarters before the event (−Q2 & −Q1), during the second quarter before the event (−Q2), during the first quarter before the event (−Q1), during the first quarter after the event (+Q1), during the second quarter after the event (+Q2), and during the two quarters after the event (+Q1 and +Q2). Panel B lists the results of equality tests within the investor group and between the two investor groups over these periods.

*Indicates significance at 10% level.

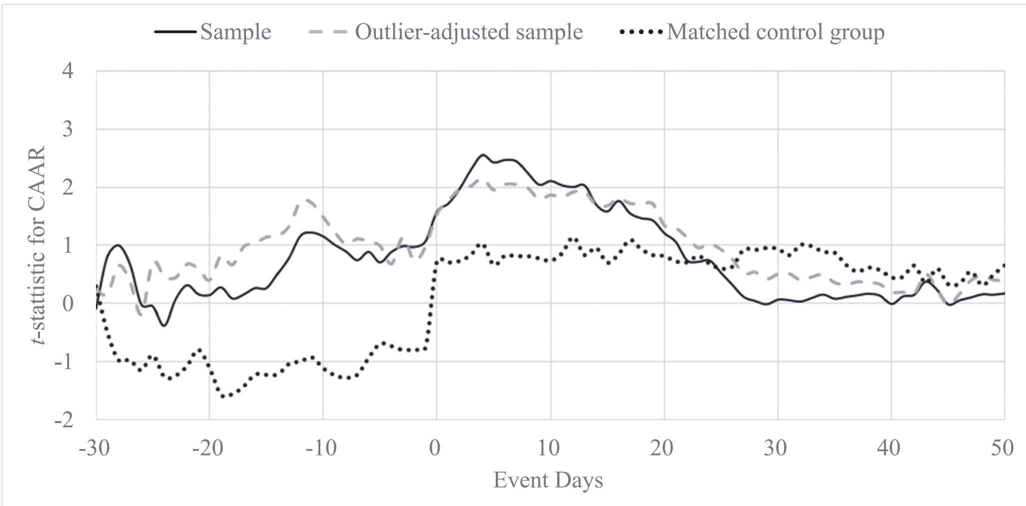
**Indicates significance at 5% level.

***Indicates significance at 1% level.

APPENDIX B

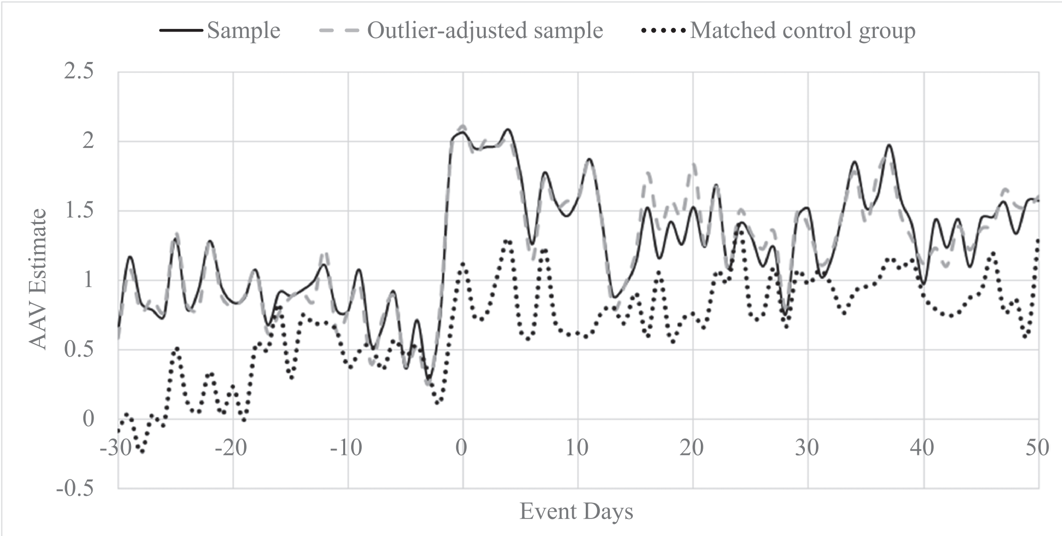


(a) Cumulative average abnormal returns (CAAR)

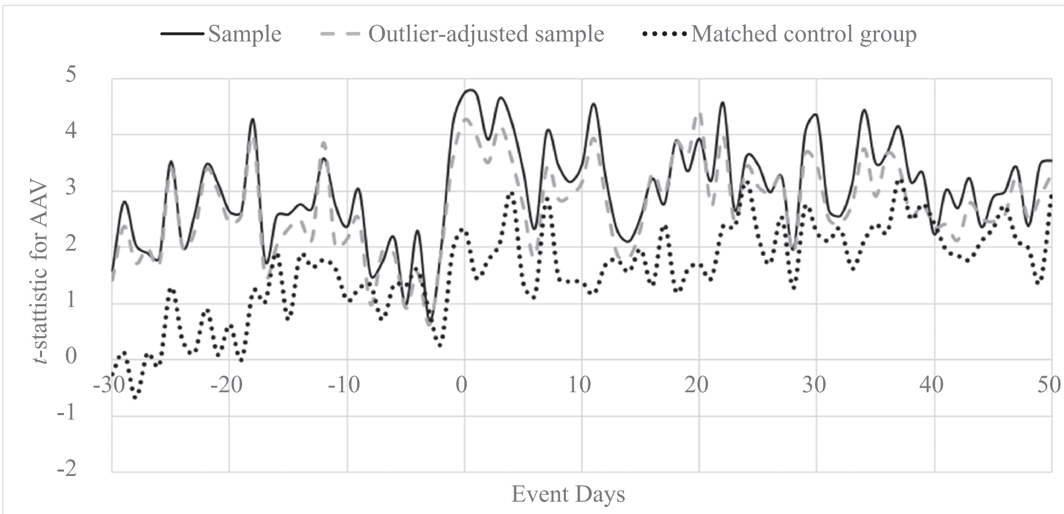


(b) ***t*****-statistics for cumulative average abnormal returns (CAAR)**

FIGURE B1 (a) Cumulative average abnormal returns (CAAR). (b) *t* statistics for cumulative average abnormal returns (CAAR)



(a) Average abnormal volume (AAV)



(b) *t*-statistics for Average abnormal volume (AAV)

FIGURE B2 (a) Average abnormal volume (AAV). (b) t statistics for average abnormal volume (AAV)