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HOW MARKETS VALUE THE BLOCKCHAIN TECHNOLOGY: AN EMPIRICAL ANALYSIS

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ABSTRACT

In this work company announcements of blockchain name changes are empirically analysed to obtain a sense of how markets value the blockchain technology. This “blockchain effect” is analysed using an event study in order to calculate cumulative abnormal returns for multiple event windows. The “blockchain effect” generates cumulative average abnormal return of 58 percent for the five days surrounding the announcement day. The effect stays stable over a +90 day post-event period and thus persists, at the least, over the short- to medium-term. No significant variations across different firm specific characteristics, such as industry or stock exchange listing, are observed. The results are robust to outliers and momentum effects, however, the results show dependency on investors’ market sentiment, that is; in market upturns, significantly greater abnormal returns are generated than in market downturns. The results show strong similarities in terms of market valuation to comparable technological innovations in the past.

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CHAPTER 1

INTRODUCTION

How do markets react to company announcements in connection with the promising and revolutionary blockchain technology? Can those reactions be meaningfully quantified? And how sustainable are those revaluations? Long Island Iced Tea Corp (now Long Blockchain Corp, LBCC), a US based small-cap beverage maker, on December 21, 2017 experienced a 300 percent jump in its share price after announcing that the company "is shifting its primary business strategy to blockchain technology" and thus changes its name to Long Blockchain Corp in order to better reflect the repositioning (Chakrabarty & Osterman, 2017). Such extreme market reactions, even for completely unrelated businesses, have become commonplace especially since the recent surge and hype in cryptocurrencies. In order to adequately classify these movements, a deeper understanding of the underlying technology and investors' behaviour is necessary.

The intrinsic idea and promise of a blockchain or distributed-ledger-technology (DLT) lies in the creation of a distributed consensus among participating parties and thus the evolution from a centralized to a decentralized economy and community overall (Berkeley University of California, 2015). Or in the words of Nakamoto (2008), one of the technologies' main (pseudonymous) sponsors: "A system based on cryptographic proof instead of trust".[1] Interestingly, with the help of Nakamodo's (2008) publication of a "Peer-to-Peer Electronic Cash System", the meanwhile well-known and most popular cryptocurrency "bitcoin" is not only is the technologies' most popular application, but it also gave birth to the wider use (beyond transactions) of the blockchain technology itself. The technology projected to have far-reaching implications on our society and will profoundly change the way our community interacts (Murphy & Stafford, 2018). Potential applications of the technology reach from financial, such as newly organized stock exchanges or ownership registration schemes for insurance companies, to non-financial, such as public notary or music patent licencing (Berkeley University of California, 2015). Short, the blockchain can be used where a

[1] Due to the financial focus of the work performed, a detailed technical explanation of the technology is neglected here. Instead, the focus is set on its overall idea and revolutionary implications for our digital interactions. Please refer to Berkeley University of California (2015) or Nakamoto (2008) for a technical explanation of the technology. However, a brief overview of the technolgoy will be outlined under "Theory & Previous Research".

centralized trusted authority can be replaced by a decentralized and anonymous peer-to-peer consensus.

However, to date, as it happens with radical innovations such as blockchain, there are still significant risks of adoption (Wild, et al., 2015). According to Wild, Arnold & Stafford (2015), the technology will still have to overcome serious hurdles in the context of security, regulation or even energy supply in order to seize its potential. Now, given that the technology is still in its infancy, the key question of this research is how investors gauge this revolutionary technological potential in terms of corporate value, and how they behave under this uncertainty in a short- to medium-term perspective.

The event study of name changes[2] allows for a specific valuation analysis of the underlying topic of the name change itself (Campbell, et al., 1997). That is, the returns generated due to a name change are most likely to be independent of contaminating events and solely the result of investors' sentiments regarding the companies' change of direction (MacKinlay, 1997). Accordingly, as performed during similar technological changes[3], the blockchain technologies' valuation implications are analysed using an event study of name changes. In particular, while focusing on the full cross-sectional sample available of the respective name changes, also industry specific factors, as well as stock exchange listing factors, are investigated. Although firm specific differences constitute valuable insights, the main focus lies on significance and magnitude of the overall abnormal returns per se. In order to get a sense of the valuation persistency profile, and to account for any leakage prior to the event, analysis will be performed for multiple post-event and pre-event windows respectively. Also, different robustness measures will be applied to the original results obtained to gauge their consistency. Finally, particular care will also be taken on the statistical accuracy and economic effectiveness in the empirical analysis of the event study in question.[4] Throughout the work, the market reactions following a company name change involving the blockchain technology will be referred to as the "blockchain effect".

[2] Please refer to section "Methodology" for an in-depth discussion regarding the methodology.
[3] Refer to section "Previous Research" for an in-depth listing of previous name change event studies.
[4] Refer to Sections "Methodology", "Data" and "Discussion and Limitations" for an in-depth discussion of the empirical work applied.

The work is organized as follows. In Chapter 2, the theory on the blockchain technology and previous research on similar issues (i.e. name change event studies of similar kind) will be presented. In Chapter 3, hypotheses will be outlined to set the basis for the empirical work later. In Chapter 4 and 5, the methodology and data for the empirical work performed are carefully outlined respectively. In Chapter 6, the detailed results based on the hypotheses build initially are outlined and the robustness tests are presented. Finally, in Chapter 7 and 8, a discussion on the explanatory power will be held and technical as well as economic limitations of the work performed are outlined.

CHAPTER 2

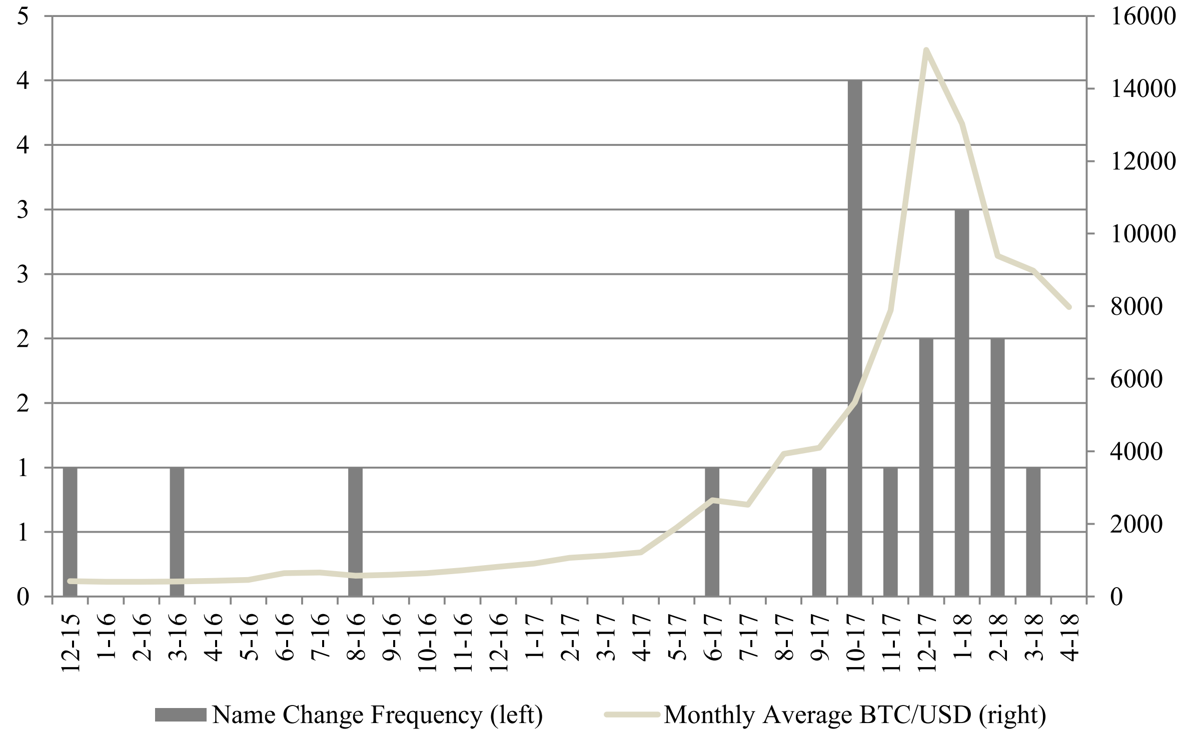
THEORY & PREVIOUS RESEARCH

This chapter aims to provide the reader with some insights about the revolutionary potential of the blockchain technology and should give some guidance about previous event studies performed in this context. To start off, the following Figure I provides a sense for the current market behaviour regarding the blockchain technology. As outlined introductory, the bitcoin (BTC) is not only based on the blockchain but also is the forerunner of the technology itself (Nakamoto, 2008). With this in mind, considering the development of the BTC/USC currency exchange rate, the recent (and still ongoing) interest and demand from investors to be associated with the technology is obvious (Murphy & Stafford, 2018).[5]

Figure I

Increasing Name Changes towards blockchain with BTC/USD Exchange Rate

Figure I shows, on the one hand, the monthly average BTC/USD prices from 12/15 until 04/18 (line, right scale), and on the other hand, the frequency of company name changes towards blockchain in the respective month over the same time horizon (bar, left scale).



[5] Note that, for simplification throughout the work at hand, when referring to the BTC/USD currency exchange rate, only the BTC is assumed to drive the exchange rate but not the USD. This is reasonable since the BTC shows similar developments using other reference currencies.

Interestingly, with the increase in the blockchain technology (identified by the BTC/USD exchange rate) by the end of 2017, as can be depicted in Figure I, company name changes towards blockchain related names increased substantially. This managerial behavior suggests some kind of rational for the name change with regards to shareholder value (Chakrabarty & Osterman, 2017), as will be examined later.

As highlighted in the introduction, a number of popular press articles have reported extremely large returns earned by such companies that changed their names to blockchain-related names (Wild, et al., 2015) (Pal, 2018) (Murphy & Stafford, 2018) (Chakrabarty & Osterman, 2017). The articles mainly suggest that the large increase in returns is due to a "mania" on the part of investors. According to the articles the mania might mainly be fuelled by (particularly short-term) investors, simply searching for stocks that let them participate in the current blockchain hype, which consequently creates a price pressure induced-bubble in these stocks. Within financial markets, long history exists reporting such manias (MacKay, 1841). From the Dutch tulip bulb craze in the 17^{th} century over the internet bubble by the turn of the millennium, as well as now suspected for the "blockchain bubble", the common feature in all these manias is, on the one hand, that they happen within industries promising revolutionary changes with a tremendous growth potential and, on the other hand, also high uncertainty (Coopers, et al., 2001).

The key question of the research at hand is now whether the "blockchain effect" can be associated to similar investor behavior in terms of market reactions and market value implications. Hereafter, the technology itself is first outlined by putting a particular emphasis on the value potential. After, the so far applied event study research in general and specifically for such name and technology announcement are outlined.

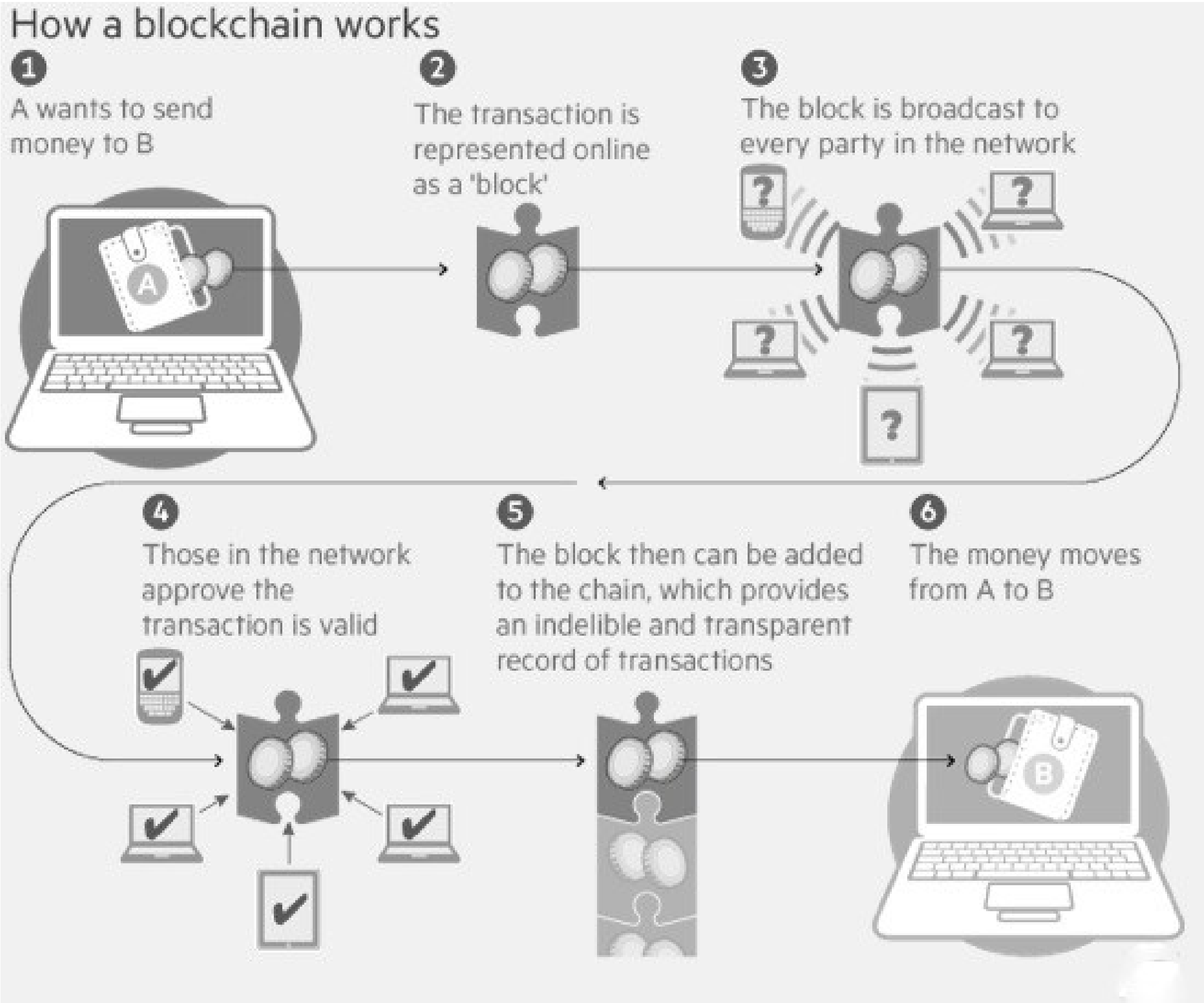
2.1. The Blockchain Technology

Without going too much into technical details, a brief illustration of the technology itself is considered beneficial for the reader in order to classify the subsequent analysis. Figure II briefly illustrates the simplified work stream of a blockchain in accordance with (Wild, et al., 2015).

Figure II

Illustration of a Blockchain Work Stream for a Financial Transaction

Figure II shows a simplified work stream of a blockchain using a financial transaction for illustrative purposes. The flow can be divided into six distinct workflows, that is; (1) desire to send money, (2) block representation, (3) broadcast in network, (4) prove by network, (5) addition to chain, (6) transfer of money.



Source: Wild, et al. (2015)

Without further investigating the individual steps (illustrated in Figure II for the case of a financial transaction), as can be observed in the work stream, the main differences to traditional financial transaction is the replacement of the third party (i.e. the trust in the third party) by the cryptographic proof using the network (i.e. trust in the crowd) (Berkeley University of California, 2015).

According to Pal, (2018), Murphy & Stafford (2018), Bekeley University of California (2015) as well as Wild, et al. (2015), precisely this shift for a centralized trusted transaction environment to decentral peer-to-peer network, where consensus is maintained by the crowd, constitutes the main revolutionary power of the blockchain technology. Potentially, they argue, the process will not only be streamlined (in the sense that less authority and thus less intermediation is needed) but also safer (as the networks' cryptographic proof is, in theory, immune to centralized fraud). Given this commonly known potential, as well as the uncertainty in the speed (of implementation), security and possible dimensions of the technology (Murphy & Stafford, 2018), it is highly relevant and contemporary how markets gauge the technology in terms of value.

2.2. Event Studies

In order to adequately quantify the effect of an event on the value of a company, the event study methodology is considered state of the art in empirical finance (Campbell, et al., 1997).[6] According to Campbell, et al. (1997), the basis and potential at the same time lies in the assumption of efficient and rational markets (i.e. stock markets), since the effect should then be immediately reflected in asset prices. They argue that another main advantage is its wide use across either firm specific (e.g. M&A) or macroeconomic events.

Event studies where reportedly first introduced by Dolley (1933) in his analysis on the effect of common stock split-ups (MacKinlay, 1997). After, according to Campbell, et al. (1997) "over the decades from the early 1930s until the late 1960s the level of sophistication of event studies increased". Mainly the consideration of confounding events and the remove of general stock market price movements were regarded as considerable improvements (Campbell, et al., 1997). In the 1980s, the today used and state of the art representations of event study methodologies arose by the implementation of the (before violated) statistical assumptions and the accommodation of more specific hypotheses (Campbell, et al., 1997). Main contributions came from Brown & Warner (1980) and their follow up work using daily data (1985) respectively (MacKinlay, 1997). Today, the event study methodologies from Brown & Warner (1980) (1985) are still very common, although, new insights on estimation methods are researched on a constant basis (Ahern , 2009).

[6] Refer to „Methodology" for an in-depth outline of the general methodology as well as the version applied in the context of the work at hand.

2.2.1. The Event Study of Name Changes

Considering name changes in general, the findings in the context of value creation are somewhat twisted. While the financial press and the financial analyst community largely argue that corporate name changes result in permanent value creation for firms and that the value of a company's name should be reflected in the company's stock price (Coopers, et al., 2001), academic research appears to find mixed results. On the one hand, Karpoff & Rankine (1994) and Bosch & Hirschey (1989) only find statistically insignificant excess returns of 0.4 percent over the 2-day and 1.62 percent over a 21-day period around the announcement day respectively (and even negative post-announcement returns, although insignificant, cancelling out the initial positive return in case of the latter). On the other hand, Agnihotri & Bhattacharya (2017), investigated a sample of 415 Indian firms, and found statistically significant cumulative abnormal returns (CARs) of 3.35 and 4.69 over a 2-day and 3-day period surrounding the event date respectively.[7] Coopers, et al. (2001) report substantial changes in firm value for dotcom name changes during a dotcom surge. Whether rational (i.e. investors' expectations on future cash flows) or irrational (i.e. speculative bubble), corporate name changes appear to be relevant during revolutionary technological changes, as will be outlined in the subsection hereafter.

2.2.2. Technology specific Name Change Event Studies

Statements such as; "the blockchain distributed consensus model is the most important invention since the internet itself", Marc Andreessen in Berkeley University of California (2015), or; "you should be taking this technology as seriously as you should have been taking the development of the internet […] it's analogous to email for money", Blythe Masters in Wild, et al. (2015), made from leading experts in the field suggest a connection between the current market reactions and the invention of the internet towards the turn of the millennium. Indeed, Pal (2018) compares the current surge in blockchain related stocks to a similar rush during the dotcom bubble.

A basis for the empirical analysis hereafter provide Coopers, Dimitrov, & Rau (2001). In their work the authors document striking positive stock price reactions following the announcement

[7] Note that, however, Arpita (2017) acknowledge that the results might be driven due to the fact that companies in emerging markets suffer from institutional voids resulting from ill-developed capital markets.

of corporate name changes to internet-related dotcom names. They find that the “dotcom effect” produces CAR in the order of 74 percent for the 10 days surrounding the announcement day. Also, they argue that this effect appears to be non-transitory, as no significant negative post-announcement drift is observed.

However, in complementary follow-up research on the valuation effects of name changes in a market downturn, that is; during the bust period of mid-2000, contrary dotcom name deletion activities have been proved to result in similar positive market reactions (Rau, et al., 2002). Thus, the overall results obtained during the internet bubble add support to investor irrationality influenced by cosmetic name change effects.

The research at hand aims to provide similar inference about the value implications of a plain blockchain related name change. Since the blockchain technology can be comparted to the internet technology (Wild, et al., 2015), investors’ behaviour in terms of market reaction is assumed to be similar. Specifically, the hypothesis regarding the reaction stated in the upcoming chapter are investigated successively.

CHAPTER 3

HYPOTHESES

The purpose of this chapter is to clearly state hypotheses in the context of the "blockchain effect", which will be tested in subsequent chapters. First, an initial hypothesis regarding abnormal returns on an overall blockchain name change announcement is formulated, which sets the basis and centerpiece of the work performed. After, in order put the overall results into perspective, subcategories are touched up. On the one hand, the leakage and persistency profile of the "blockchain effect" is projected. On the other hand, industry and exchange listing specific cross-sectional differences are formulated. Finally, various robustness assumptions for the formulated hypotheses are stated.

3.1. Abnormal Returns on a Blockchain Name Change – the "Blockchain Effect"

The predictions for a "blockchain effect" follow the findings regarding the "dotcom effect" outlined earlier (Coopers, et al., 2001). Given the comparable technological implications and market behaviors, blockchain name changes are assumed to earn statistically significant abnormal returns in the short-term perspective. That is, cumulative average abnormal returns (CAARs) of the entire cross-sectional sample are expected to indicate a high value premium for the days closely surrounding the event day (i.e. event windows 0 to 1 and -2 to +2, as outlined in detail later). Thus the following hypothesis is stated:

H1: A firm's name change towards the blockchain technology is associated with abnormal returns significantly different from zero.

3.2. Persistency and Leakage[8] Profile of the "Blockchain Effect"

In the face of the suspected bubble effect regarding the recent market behavior in the context of the blockchain technology (i.e., among others, the recent surge and increased volatility in the BTC/USD currency rate), the question whether abnormal returns following a blockchain name change persist post-event is of great interest. According to the reviewed "dotcom effect", technologically motivated excess returns following a name change are likely to persist, at least in the medium-term perspective (i.e. ca. +120 days following an event date) (Coopers, et al., 2001). However, in the long run, and especially given a backlash associated with the technology in question, market valuations are likely to settle on a normal level (Rau, et al., 2002).

Thus, CAARs are not only assumed to be highly positive and statistically significant in the days around the event date, they are also predicted to persist during a +1 to +30, +1 to +60 and a +1 to +90 post-event window. That is, although no (additional) statistically significant CAARs are expected, the initially gained excess returns are not expected to decrease significantly and thus stay stable in the post-event window. Hence, the following hypothesis can be stated:

H2: CAARs persist over the post-event windows of up to +90 days following the event (day 0).

Several factors can cause positive pre-event abnormal returns.[9] The most common one is leakage of event relevant information, causing the market to react pre-announcement of the actual news (Campbell, et al., 1997). Given the relatively small-capitalized sample firms and the minor analyst and news coverage of the firms in question, the following hypothesis is stated regarding leakage:

H3: No statistically significant abnormal returns are observable over a pre-event window of -15 to -2 day prior to the event (day 0).

[8] Leakage is referred to information regarding the event being available for (some) investors prior to announcement (Campbell, et al., 1997).
[9] Note that, reasons such as the actual announcement date being before the defined event date (Coopers, et al., 2001), or that the respective subsample companies have high betas, are neglected in the scope of the work at hand. However, be aware that presence of such circumstances would bias the results towards accepting the null hypothesis of no abnormal performance.

3.3. Differences among Industries and Stock Exchange Listings

One might suspect companies that were already active in technological industries to earn lower or no abnormal returns, as the involvement with blockchain is somewhat expected for this kind of firms opposed to companies not involved in the technology at all. However, according to the assumed mania behavior of investors in relation to the blockchain, and thus a suspected casual and rough fundamental analysis prior to investing, no significant differences are expected among different industries. Investors are assumed to focus on the simple involvement in the blockchain technology and the actual underlying industry (and i.e. revenue generating rational) to play a minor role (Coopers, et al., 2001). Hence, the following is stated:

H4: CAARs of industry baskets are expected to not significantly differ among each other for event windows closely around the event date.

Similarly, no statistically significant differences in CAARs is expected among different stock exchange listings of the individual firms. Although firms from the OTC Markets are, on average, smaller capitalized and might thus potentially profit from micro structure issues[10], market reactions on name change announcements are assumed statistically immune to stock exchange listing effects.

H5: CAARs of listing baskets are expected to not statistically significantly differ among each other for event windows closely around the event date.

3.4. Potential Trading Strategies

A brief analysis will be performed on whether the "blockchain effect" provides a profitable (short-term) trading strategy. Given the observed and empirically expected speculative reactions, the name change announcements might be driven more by short-term profit intentions rather than long terms value considerations. The following is assumed:

[10] Refer to section „Limitations & Discussion" for an in-depth analysis of this issue.

H6: CAARs are assumed to be positive in the days shortly following the name change event and thus provide a short-term profitable training strategy

3.5 Robustness of the "Blockchain Effect"

As only a relatively small sample size is available and returns are expected to be increasingly volatile around the name change event (also because of the mainly small capitalized firms), various robustness checks are implemented to support the findings. The focus will be put on an outlier, momentum as well as investor sentiment analysis.

3.5.1. Robustness to Outliers

As outlined before, highly extreme market reactions are suspected around a blockchain related name change announcement and thus returns are expected to be increasingly volatile (Boehmer, et al., 1991). Given those circumstances, one is interested in the robustness of the initial cross-sectional analyses if outliers are excluded from the data. The following hypothesis is stated in the context of outlier analysis:

H7: The results are robust to outliers beyond the 95th and below the 5th percentile of individual time series returns. That is, excluding those outliers does not significantly change the results regarding the "blockchain effect".

3.5.2. Momentum Effect

One possible explanation for high abnormal returns earned by a name change may simply be that they are due to momentum[11]. That is, firms with high abnormal returns before the name change announcement continue to have high returns after the name change. However, in the work at hand, abnormal returns are assumed to be solely associated with the firm specific name change rather than market momentum. Thus, the following is stated:

[11] Note that, for clarification, with the term „momentum" the individual firm specific momentum, rather than the market momentum, is analyzed.

H8: Pre-event market returns are uncorrelated to post-event stock returns and thus the CAARs are not a consequence of firm specific momentum.

3.5.3. Shifts in Investor Sentiment

Given that the blockchain technology is still in its infancy, and investors are still learning about its true growth and value potential (Wild, et al., 2015), the blockchain related market sentiment is assumed to play a major role in explaining CAARs. Also, this hypothesis is supported by the assumption that companies change their names in accordance with the blockchain technological hype cycle (Pal, 2018). The BTC/USD currency exchange rate is considered an adequate measure for investors' blockchain sentiment.[12] Thus, the following hypothesis is stated:

H9: Investors' blockchain sentiment determines CAARs from the name change. Specifically, CAARs are expected to be significantly greater when the name change event happenes during months with high BTC/USD returns.

Having defined the nine hypotheses as a basis for the research, now, the methodology of the empirical work can be outlined accordingly. Note that not all the methodologies for the stated hypothesis are outlined in the subsequent chapter, but rather the focus is put on the general event study methodology. However, specific robustness methods or alike will be presented in detail within the respective results section.

[12] Recall that the Bitcoin is not only directly associated with the technology, but also builds its foundation in terms of other applications (Nakamoto, 2008).

CHAPTER 4

METHODOLOGY

This section introduces the reader to the specific event study methodology applied for the empirical analysis of the "blockchain effect" in this work.[13] The following is a standard procedure (compacted, for simplification) of an event study return analyses in accordance with (Campbell, et al., 1997).[14] (1) Event definition: Precise definition of event and the time horizons (might be multiple event windows) over which the security prices should be analysed. (2) Selection criteria: Defining the exact criteria for companies that should be included in the sample. (3) Measuring normal and abnormal returns: Measuring the normal performance first, that is; the returns that if the event did not take place, using the estimation window as a basis. And inferring the abnormal performance subsequently from the normal performance using the event window. (4) Testing abnormal returns: Given the estimated parameters of the normal performance model, one can calculate the abnormal returns and also test the (cumulative) abnormal returns on their statistical significance (usually using parametric methods).

Note that the first two standard steps of an event study according to (Campbell, et al., 1997), are neglected in this section and will be touched up later under "Data". Also, for illustrative purposes, specific data used in the analysis (e.g. the market index used in the analysis) will be discussed in the subsequent "Data" section.

The methodology for performing the event study in the work at hand is in accordance with Brown & Warner (1980) and their follow up analysis using daily stock returns (1985) respectively. A market model in accordance with Campbell, et al. (1997) is used to measure normal performance and thus to define abnormal excess returns.[15]

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[13] Note that, however, a brief understanding of the event study terminology (e.g. estimation and event window etc.) is assumed from the reader in order to follow the argumentations outlined in this section. Refer to (Campbell, et al., 1997) for an in-depth explanation.

[14] Note, however, that this process is standardized for an individual security observation. In the analyses at hand, CAAR instead of CAR are used to evaluate the cross-sectionally aggregated abnormal returns and the procedure changes slightly as outlined below.

[15] According to Brown & Warner (1985), Ahern (2009) as well as Campbell, et al. (1997), the OLS market model provides the best estimate for normal return performance. That is, more variations of the individual security can be explained by the model vis-à-vis of using a simple constant mean model and obtained inference is thus more powerful.

First, in order to evaluate the normal performance of each company, the cross-sectional sample of daily stock returns is analysed individually. In particular, the returns from the estimation window of the individual stocks are regressed on the respective market returns using the following equation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} .$$

After, the obtained estimation coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ from the regression above are used to calculate the expected normal returns as follows:

$$E\{R^*_{it}|\Omega_{it}\} = \hat{\alpha}_i + \hat{\beta}_i R^*_{mt} ,$$

where * indicates that the returns are from the event window and Ω_{it} states that the returns are conditional on stock information in the estimation window (i.e the conditioning information for the normal performance model). After, abnormal returns are calculated by simply the difference between realised returns in the event window and the predicted normal returns:

$$AR_{it} = R^*_{it} - E\{R^*_{it}|\Omega_{it}\} .$$

By aggregating the abnormal returns within the event window, cumulative abnormal returns (CAR) are calculated for every individual sample observation. [16]

$$CAR_{ik} = \sum_k AR_{it}$$

Next, as one is interested in the cross-sectionally aggregated representation of CAR over the different event windows and only want to focus on the mean affect, cumulative average abnormal returns (CAAR) are calculated in the following way[17]:

[16] k in this context comprises the length of the event window in consideration as well as the start and end point of the respective window (e.g. event day 0 to 1, or day -15 to -2). A mathematically more accurate definition of abnormal returns in matrix notation can be obtained in Campbell, et al. (1997).

[17] Note, again, that this represents a loose and practical definition of CAAR. For a mathematically more accurate version using matrix notation refer to Campbell, et al. (1997).

$$CAAR_k = \sum_i CAR_{ik}\,.$$

Finally, in order to draw statistical inference, the variance (and i.e. the standard deviation) of the different CAAR is elaborated and the CAAR is standardized using the estimated standard deviation:

$$\hat{\sigma}_{CAAR_k} = \sqrt{\frac{1}{i(i-d)}\sum_i (CAR_{ik} - CAAR_k)^2}\,,$$

$$t = \frac{CAAR_k}{\hat{\sigma}_{CAAR_k}} \sim N(0,1)\,.$$

Brown & Weinstein (1985) find, using a variety of estimation procedures and experimental designs, that a factor model adds limited value to the use of a simple market model and consider the latter as most effective to identify true abnormal returns. Also, all else equal, Brown & Warner (1985) find that event study methodologies based on the OLS market model and using standard parametric tests are well-specified under a variety of conditions.[18] The OLS market model systematically outperforms the mean adjusted return model (i.e. constant-mean-return model in Campbell, et al. (1997) terminology) and the market adjusted return model[19] (i.e. the adjusted market model) in terms of statistical power. Moreover, they find "no clear-cut benefit in detecting abnormal performance using estimation procedures other than OLS for market model" (also in the presence of clustering or non-synchronous trading). Thus, the OLS market model for the estimation of normal performance is considered reasonably well-specified for the detection of the "blockchain effect" in the work at hand.

Considering the hypotheses stated before, one is also interested in whether or not the CAARs among different subcategories are significantly different from each other. In order to test whether the two or multiple CAARs are significantly different from each other a F-test is used for the parametric approach in the context of this work (Brooks, 2014). The methodology used for the "blockchain effect" analysis is in accordance with Maddala & Lahiri (2009) and Brooks (2014).[20]

[18] Refer to section „Limitations & Discussion" for an in-depth listing of the conditions.
[19] Where $\hat{\alpha}_i = 0$ and $\hat{\beta}_i = 1$.
[20] Refer to those references for a detailed methodology of the F-test.

CHAPTER 5

DATA

The sample consists of daily stock returns from publicly traded companies on the New York Stock Exchange (NYSE), NASDAQ, American Stock Exchange (AMEX), London Stock Exchange (LSE), Hong Kong Stock Exchange (HKG), Tel Aviv Stock Exchange (TLV) as well as various OTC Markets (OTCQX, OTCQB, OTCBB and all the Pink subsections).[21] Note that, although a considerable amount of sample data from companies listed on the grey market is available, this from of data is not included in the sample due to quality issues (i.e. trading frequency, stock splits etc.). The sample consists of listed companies that experienced a "name change in relation to the blockchain technology" between 31/12/2015 and 3/6/2018. A name change is considered "in relation to the blockchain technology" if at least one of the following words are added (or replaced) to (with) the previous company name: "Blockchain", "Bitcoin", "Crypto" or "Chain".[22] The critical event date, that is; the data of the announcement of the name change, is obtained using various news websites, Google filter options as well as the US Security and Exchange Commission (SEC) filings.[23] In order to classify the sample companies into different industry categories, published company profiles, SEC filings, contemporaneous news releases as well as the company webpages are consulted.

In many cases, information on the actual announcement date is difficult to obtain with certainty. As a result, the earliest announcement date coincides with the effective date, that is; the date when the firm actually started trading under the altered name. Due to this difficulty in obtaining exact announcement dates for some of the sample stocks, the announcement day is defined as the first information available on the name change (regardless of whether from an effective or announcement trading day). Given that the actual announcement day is likely to be before the date used in the data at hand, estimates are biased towards accepting the null hypothesis of no abnormal "blockchain effect" returns in the event window (Campbell, et al.,

[21] Refer to Appendix I for an overview of data sources utilized in the study.
[22] Note that "Chain" is only considered if it is related to the blockchain technology. The respective sources in the Appendix I are used to research the intended meaning of the word. Note that the words are chosen according to the Internet words for the "dotcom effect". Refer to Coopers, et al. (2001).
[23] Refer to Appendix I for an overview of data sources utilized in the study.

1997).[24] Due to this issue of potential information leakage, a pre-event window of -15 to -2 is equally considered in the analysis.

The sample consists of 18 publicly traded companies of which 13 are listed on OTC markets and 5 on the other mentioned stock exchanges. Table I briefly illustrates the sample used to investigate the "blockchain effect".

Note that, although the cross-sectional sample size is relatively small, generally, the specification of the test statistics for daily stock returns should not be dramatically altered for daily stock returns (Brown & Warner, 1985). Also, Ahern (2009) and Jung (2006) find that simple estimation techniques are well specified, even for small sample sizes. In particular, Jung (2006) finds the following after analysing the effect of small sample size problems on the power of the tests in event study methodologies: (1) even for a sample size group of 20 the empirical and test statistics distributions seem close to normal and unit normal respectively, regardless of the normal performance model applied. (2) given a certain level of excess returns, the probability of Type II error[25] and thus the power of the test[26] decreases. (3) Given no event date clustering (i.e. no overlapping of event windows), using the share time series method (as suggested above), in contrast to the portfolio time series method, improves the power of the test for cross-sectional sample sizes greater than five. According to Jung's (2006) findings, one can conclude that for the sample size at hand (18 securities), the small sample size problems are, in general, not serious enough to distort empirical results in the event study. Also, by using a relatively small sample size, the results on abnormal performance are generally biased towards falsely rejecting the null hypothesis and are thus more conservative.

[24] This is because the non-event period does not provide an unbiased estimate of what the security return would have been in absence of the event (i.e. the normal performance is „too high" and thus abnormal returns are smaller).

[25] I.e. the error to fail to reject the null hypothesis of no excess returns when it is false (i.e. when there are actually excess returns) (Brooks, 2014).

[26] Power of the test = [1 – probability of Type II errors] (Brooks, 2014).

Table I

Description of the Sample

This table describes the sample of companies that changed their names to blockchain names between 12/31/2015 and 04/20/2018. In Panel A, given the manageable sample size of 18 observations, the companies are briefly introduced in the context of the underlying event study. In Panel B, firms are divided into subcategories based on their industry and stock exchange belonging. The categories for the Industry are: Technology, Financial Services, Consumer, Commodity and all other undefined industries. The categories for the Stock Exchange Listing are: OTC listed and other stock exchange listings. Because of the difficulty in obtaining exact announcement dates, the announcement day (day zero) is defined as the first available information on the name change, whether from an announcement or effective trading day. Also, note that, industry belongings are summarized into broad high level industries for simplicity and sample size reasons.

Ticker	Name	Event Date	Industry	Listing
364	Blockchain Group	10/27/2017	Consumer	Other
BCII	Blockchain Industries	11/15/2017	Other	OTC
BITCF	First Bitcoin Capital	08/15/2016	Commodity	OTC
BLCM	Blockchain Mining	10/17/2017	Commodity	Other
BLCS	Blockchain Solutions	03/06/2018	Financial Services	OTC
BLKCF	Global Blockchaini Techonolgies	09/28/2017	Financial Services	OTC
BLOC	Blockchain Worldwide	01/22/2018	Financial Services	Other
BTSC	Bitcoin Services	03/15/2016	Technology	OTC
EVBC	Evolution Blockchain	02/27/2018	Other	OTC
HVBTF	HIVE Blockchain Technologies	06/14/2017	Commodity	OTC
LBCC	Long Blockchain	12/21/2017	Consumer	OTC
MBLC	Millennium Blockchain	01/18/2018	Other	OTC
NODC	Nodechain	12/20/2017	Consumer	OTC
NXCN	NXChain	12/31/2015	Other	OTC
OBC	Online Blockchain	10/26/2017	Technology	Other
RIOT	Riot Blockchain	10/04/2017	Technology	Other
SRTI	SRTI Blockchain	02/12/2018	Technology	OTC
VRCP	Virtual Cryprto Technologies	01/19/2018	Other	OTC

	# of sample companies
Initial number of firms in sample	31
Total remaining firms after deletion[27]	18
Companies by Industry:	
- Technology	4
- Financial Services	4
- Consumer	3
- Commodity	3
- Other	4
Companies by Listing:	
- OTC	13
- Other	5

[27] That is, contaminating events such as trading frequency, stock splits ect. Or other data quality issues mentioned (i.e. trainding frequency, unclear event date, illiquidity ect.)

Price data is collected for the 196-day period surrounding the respective event from -105 to +90 for the sample of 18 firms.[28] The estimation window is defined as -16 to -105. The following event windows will be separately analysed on CARs: (1) -15 to -2; (2) 0 to 1; (3) -2 to +2; (4) +2 to +15; (5) +1 to +30; (6) +1 to +60; (7) +1 to +90. The reason why seven distinct event windows are analysed is to get a better sense of the leakage as well as the valuation persistency profile of the "blockchain effect". Particularly the post-event windows (5), (6) and (7) will be of interest when analysing valuation persistency of blockchain name announcements. Also, as aforementioned, since the true announcement date is difficult to obtain, the various event windows provide wider coverage of returns around the event date. However, using longer event windows also poses certain issues which will be discussed in a later section.[29]

In order to estimate abnormal returns using the OLS market model, a suitable benchmark index must be defined. In the case at hand, the OTC Market Composite Index is considered for the market returns. As most of the sample companies (i.e. 13 of the totalling 18) are listed on the OTC market, and were active in a widely diversified range of industries prior to the name change, the OTC Composite Index is considered a good benchmark to construct the normal performance for the overall cross-section. Note that, no "Blockchain Index" or alike is taken into consideration for the market returns since one is interested in the change from a "normal" industry to blockchain (via the change of name). Thus, a wider industry index is deemed accurate to extract abnormal performance of the "blockchain effect" vis-à-vis normal performance.

In order to obtain a truthful picture of abnormal returns, daily prices are adjusted for contaminating events such as mergers, issuance of stocks, earning announcements or stock splits during the event window periods. Also, companies with a lack of data or insufficient liquidity or highly uncertain event dates are excluded from the sample. Note that, as data is gathered from different jurisdictions, inconsistent day counting results among the different stock exchanges. Given those issues, as well as the circumstance of small capitalization companies, it is difficult to obtain current stock price information and a fully consistent

[28] Note that not all the sample firms have enough data observations provided (especially in the post-event window). However, as the required data criteria is fulfilled, the securities are included in the sample anyway but treaded separately in the respective event window. Naturally, the missing observations are accounted for in the „Results" section.
[29] Refer to section „Limitations & Discussion" for a detailed analysis of long term-term inference in event studies.

estimation of abnormal returns among the different companies.[30] However, the associated normal return biases and inconsistencies with regards to non-synchronous trading are minor and can mostly be neglected (Brown & Warner, 1985).[31]

One of the critical assumptions in event studies when cross-sectionally aggregating CARs from different event windows is that the abnormal returns on individual securities are uncorrelated in the cross-section (Bernard, 1987). According to Campbell, et al. (1997) this assumption is generally given if event windows of the included securities do not overlap in time, that is; no clustering of event windows. If this assumption is fulfilled, it allows for the variance calculation of the aggregated CARs (i.e. CAARs) without concerns about covariance between individual sample CARs. In other words, unbiased distributional results and thus meaningful statistical inference can be assumed without clustering of event windows. However, as in the case at hand the event windows partially overlap, the following Table II showing a correlation matrix of the sample abnormal returns is calculated to investigate the issue of cross-sectional dependence:

Considering Table II below, the average absolute correlation among the sample companies' abnormal returns is 0.092 with no firm exceeding a correlation of 0.55 (in absolute value). Hence, the assumption of cross-sectionally independent CAAR variance estimations in the context of the "blockchain effect" analysed in the subsequent section can be confirmed.[32]

To conclude, by making the appropriate choice of the significance test in in accordance with Jung (2006), the potential small sample size problems faced by using the 18 observations at hand (and particularly when dividing the overall sample into subsamples), can be solved. Finally, note that the results of the event study presented hereafter are calculated using Microsoft Excel.

[30] Note that, for that reason, it is difficult to obtain current stock price information and company profiles from traditional academic source. Consequently, most of the sources on these companies are from the Internet. Refer to Appendix I for an overview of data sources utilized in the study.
[31] Refer to section "Limitations" for further clarification on non-synchronous trading and general time-series estimation issues
[32] And thus, no remediation methods, such as a portfolio consolidation of the securities in accordance with Campbell, et al. (1997) or an analysis without aggregation, as suggested by Schipper & Thompson (1983), are necessary.

Table II

Correlation Matrix of Abnormal Returns

Table II shows the correlation between the time-serial abnormal returns of the 18 sample stocks. Note that, due to the fact that the time window, for which the abnormal returns are calculated, is not the same across all securities. This is attributable to the stated fact that recent name changes do not provide a +90 or even +60 post-event window to date. In such as case, however the correlation was simply calculated for the overlapping event time provided.

	364	BCII	BITCF	BLCM	BLCS	BLKCF	BLOC	BTSC	EVBC	HVBTF	LBCC	MBLC	NODC	NXCN	OBC	RIOT	SRTI	VRCP
364	1,0	0,0	0,1	-0,1	0,1	0,1	0,2	-0,2	0,1	0,0	-0,1	0,0	0,1	0,2	0,0	0,0	0,0	0,1
BCII		1.0	0,1	0,0	-0,1	0,2	0,1	0,2	0,1	0,0	0,0	-0,2	-0,1	0,0	0,1	0,0	0,0	0,2
BITCF			1.0	-0,1	0,0	-0,1	0,1	0,0	0,2	-0,1	0,0	0,0	0,2	0,0	0,0	0,0	0,1	0,1
BLCM				1.0	-0,1	0,1	0,0	0,1	0,0	0,0	-0,1	0,0	-0,2	0,3	0,0	0,0	-0,1	-0,1
BLCS					1.0	-0,1	-0,1	-0,1	0,0	0,0	0,0	-0,1	0,0	0,0	0,0	0,0	0,0	-0,1
BLKCF						1.0	0,1	-0,1	0,0	-0,1	0,1	0,0	0,1	0,0	-0,1	-0,1	0,0	0,2
BLOC							1.0	-0,1	0,1	0,0	0,3	0,3	0,1	0,0	0,1	0,0	0,4	-0,1
BTSC								1.0	0,2	-0,1	0,0	-0,1	-0,1	0,0	0,3	0,0	0,0	0,0
EVBC									1.0	0,0	0,0	-0,1	0,0	0,0	0,2	0,1	-0,1	-0,1
HVBTF										1.0	0,0	-0,1	0,0	0,0	-0,1	0,0	0,0	0,0
LBCC											1.0	0,6	0,1	-0,2	0,0	0,0	0,5	0,2
MBLC												1.0	0,0	-0,3	-0,1	0,1	0,5	0,1
NODC													1.0	0,0	-0,1	0,0	0,1	0,1
NXCN														1.0	0,0	0,0	-0,4	-0,1
OBC															1.0	0,0	0,0	0,0
RIOT																1.0	0,0	0,0
SRTI																	1.0	0,2
VRCP																		1.0

CHAPTER 6

RESULTS

The aim of this results section is to test and analyze the hypotheses stated earlier, using the methodology outlined in the preceding section. Therefore, this section will be built-on analogous to the hypothesis section and tests will be performed in accordance to the stated assumptions. Starting off with some descriptive statistics, the hypotheses will be analyzed successively.

6.1. Descriptive Statistics

As depicted in Figure I, no event study relevant blockchain name change was found prior to December 2015. Also, the name change frequency dramatically increased by the end of 2017 relative to the prior years with an average monthly blockchain name change frequency of 1,4 between July 2017 and April 2018 compared to only 0,2 between December 2015 and June 2017. 78% of the sample firms announced their blockchain name change in the later time period. Again, as outlined earlier, this clearly indicates a tendency of name changes with the surge in BTC/USD.

Considering (as a starting point for the more sophisticated empirical approach hereafter) raw price and volume data of the sample companies, a clear positive evolution of both can be observed between the pre- and post-event period. Specifically, the average overall cross-sectional share price increased from 7.69 15 days prior to the announcement[33] to 21.93 15 days post-announcement, yielding an overall cross-sectional compound annual growth rate (CAGR) of 3.55 percent. Note that, interestingly, already at this absolute and raw price level, no major differences between small capitalized OTC listings and other, lager capitalized, company listings can be observed, with average OTC stocks increasing from 0.70 to 1.68 (CAGR of 3%) and others increasing from 25.88 to 74.58 (CAGR of 3.6%) respectively. Thus, by only considering raw descriptive statistics, some general evidence to accept *H5* of

[33] Note that, with announcement, it is referred to the specified event date (day 0) in the context of the event study.

CAARs from different listing baskets not being significantly different from the cross-sectional total sample. By briefly considering the volume evolvement, a similar picture is obtained. Overall average trading volume increases from 438’137 to 1’369’930, resulting in a CAGR of 3.87 percent. Here, as expected, listing differences exist in relative terms given the small capitalizations of OTC listed firms. The volume of OTC listed firms increase from 16’029 to 165’001 (CAGR of 8.1&) on average, while firms listed on other stock exchanges report an average volume increase from 1’535’618 to 4’502’745 (CAGR of 3.7%) from event days -15 to +15 respectively.

6.2. Abnormal Returns on a Blockchain Name Change – the “Blockchain Effect”

Table III states cumulative average abnormal returns (CAAR), calculated using an OLS market model too derive normal performance. As discussed, the OTC Markets Composite Index is used as a benchmark for the market. The CAARs are calculated using various event windows for companies that change their names to blockchain related names between 12/31/2015 and 04/20/2018 (Panel A). The CAARs are also calculated for multiple sample subcategories, that is; industry specific subsamples (Panel B) divided into companies belonging to the sector Technology, Financial Services, Consumer, Commodity and all other undefined industries. Additionally, the sample is divided into stocks listed on OTC stock exchanges and the rest of the stock exchanges outlined under data (Panel C). Each cell within the table reports the CAAR across firms for the respective event windows (and subcategory, if applicable) as well as the associated t-statistic in parentheses below the CAAR. Note that, bold values within the parentheses indicate that the respective CAARs are statistically significant on a 5% level of significance (i.e. t-statistic greater than 1,96). Finally, an F-statistic of statistically different CAARs over different subcategories is depicted at the end of Panel B and Panel C for the subcategories in question (i.e. the respective p-value).

Table III

OLS market model CAARs using the OTC Markets Composite Index

This table reports cumulative average abnormal returns (CAAR), expressed in percent, and calculated using an OLS market model to derive normal performance. The underlying market index for the calculation of the market returns is the OTC Markets Composite Index. The CAARs are calculated for various event windows for companies that change their names to blockchain names, between 12/31/2015 and 04/20/2018. Each cell reports the CAAR across all firms for the respective event windows. T-statistics are reported in parentheses. T-statistics significant at the five percent level are bold (i.e. t-statistic greater than 1.96). The CAARs are calculated for multiple sample subcategories, that is; industry specific subsamples (Panel B) divided into companies belonging to the sector Technology, Financial Services, Consumer, Commodity and all other undefined industries. Additionally, the sample is divided into stocks listed on OTC stock exchanges and the rest of the stock exchanges outlined under "data" (Panel C). P-values for tests of the null hypothesis of equality of means across firm categories using an F-test are reported at the end of Panel B and Panel C for the respective subsamples.

	Event Period						
	1	2	3	4	5	6	7
	-15 to -2	0 to 1	-2 to +2	+2 to +15	+1 to +30	+1 to +60*	+1 to +90*
	CAARs according to OLS market model						
All (#18)	33 (1.88)	34 (**3.26**)	58 (**3.37**)	14 (0.89)	44 (1.30)	34 (0.97)	39 (1.00)
	CAARs according to OLS market model by Industry						
Technology (#4)	24 (**2.25**)	55 (**2.39**)	58 (**4.33**)	-17 (1.29)	27 (0.84)	60 (1.30)	31 (0.75)
Financial Services (#3)	28 (1.03)	14 (1.15)	29 (**2.00**)	67 (1.93)	80 (**2.14**)	63 (1.38)	50 (1.12)
Consumer (#4)	77 (1.81)	52 (1.86)	128 (**2.25**)	50 (1.47)	49 (0.52)	12 (0.10)	-24 (0.20)
Commodity (#3)	-3 (1.56)	18 (1.78)	24 (**2.31**)	29 (1.01)	122 (1.02)	90 (1.23)	233 (**4.63**)
Other (#4)	30 (0.52)	20 (1.10)	36 (1.38)	-40 (1.43)	-31 (0.88)	-35 (0.90)	-44 (1.08)
F-test (p-value)	0.775	0.637	0.316	0.179	0.758	0.852	0.256
	CAARs according to OLS market model by Listing						
OTC Markets (#10)	41 (1.72)	34 (**2.88**)	63 (**2.74**)	11 (0.53)	17 (0.49)	3 (0.08)	13 (0.26)
Other (#8)	13 (1.52)	33 (1.57)	45 (**3.13**)	23 (1.23)	113 (1.58)	112 (**2.34**)	107 (**2.02**)
F-test (p-value)	0.007	0.292	0.050	0.155	0.175	0.333	0.296

*For the post-event windows (6) and (7), not a full cross-sectional sample of 18 observations is available due to the fact that some companies have changed their names in the very recent past, and consequently no +60 or even +90 post-event window can be provided. This is the case for 3 companies in the case of event window (6) and 7 companies in the case of (7). However, findings are assumed to stay unchanged. .

As can be interpreted from Table III, CAARs are consistently positive across all event windows in the overall cross-section. As expected, with 58 percent, the CAAR is highest within the event windows (3) closely surrounding the event day. Although pre- and post-event windows also indicate high positive abnormal returns (e.g. 33 in the pre-event window (1) and 44 in the post-event window (5)), only the event windows (2) and (3), which closely surround the announcement of the name change, report statistically significant returns (with t-statistics of 3.26 and 3.37 respectively). Thus, the *H1* of *a firm's name change towards the blockchain technology being significantly associated with abnormal returns generated by virtue of the name-change announcement* is supported by the data and can be accepted.

6.3. Persistency and Leakage Profile of the "Blockchain Effect"

Focusing on the post-event windows (4), (5), (6) and (7) first, insightful inference regarding the persistency profile of the blockchain effect can be extracted from the table above. Although the CAARs in the respective windows are consistently positive for the overall cross-section, the abnormal returns are not statistically significant. However, given the returns are positive and statistically insignificant, the *H2* of *persistent CAARs over the post-event windows of up to +90 days following the event* can be accepted.

Also, note that no differences regarding the finding on *H2* are witnessed by observing the subsample CAARs of the post-event windows. While strong statistical evidence (although not necessarily on a 5% level of confidence) for positive abnormal post-event returns is given for other than OTC listed firms and companies active in the Commodity industry, no significant negative abnormal returns can be observed throughout all the subsamples. Also, the F-test of differences in mean abnormal returns across post-event windows within subsample companies is statistically insignificant and consequently the null hypothesis of no differences is accepted. Thus, the *H2*, and the assumption that the "blockchain effect" persists in the medium run perspective, is confirmed even when accounting for company specific characteristics.

Considering event window (1), inference regarding the leakage profile of announced blockchain name changes can be drawn. Note, however, as discussed previously, that positive pre-event returns can also be associated by other factors than information leakage alone. Given the positive 33 percent CAAR in the overall cross-sectional sample, there appears to be some evidence of information leakage for the "blockchain effect". Although the CAAR is not statistically significant on a 5% level (indicated by the t-statistic of 1.88), there appears to be a decent amount of statistical evidence for pre-event abnormal returns. Evaluating the subsamples, interestingly, the OTC listed stocks appear to have a more severe leakage issue than (higher capitalized) stocks from other stock exchanges. With a CAAR of 41 percent and a t-statistic of 1.72 for the first, and a CAAR of 13 percent and a t-statistic of 1.52 for the latter, OTC listed sample firms not only earn greater pre-event abnormal returns, but also statistically more significant ones. This finding is also supported by considering the F-statistic of differences in mean with a p-value of 0.007. Given the greater analyst and news coverage of companies other than the relatively small-capitalized ones listed on OTC markets, this result makes intuitively no sense.[34] Considering Figure III below, one can observe, within the -15 to 0 event period, that the market gradually learns about the forthcoming company blockchain name change announcements, across all sample and subsample firms. Anyhow, given the insignificant abnormal returns not only of the overall cross-sectional sample, but also within the subcategories (except for Technology, however, there the F-statistic of mean equality is accepted), the *H3* of *no statistically significant abnormal returns being observable over a pre-event window of -15 to -2 days prior to the event* is accepted.

6.4. Differences among Industries and Stock Exchange Listings

Figure III graphically presents and confirms the results outlined in Table III. The Figure shows the evolution of various cross-sectional CAAR setups by continuously accumulating the abnormal returns staring from day -15 up until +90.[35] Besides the various cross-sectional subsamples discussed under Table III, the following returns are added to this graphical representation: Cumulative raw returns and CAAR representing the full cross-sectional sample without the top 95th percentile and the bottom 5th percentile of time-series abnormal returns during the event period, that is; "Mid90 CAARs".

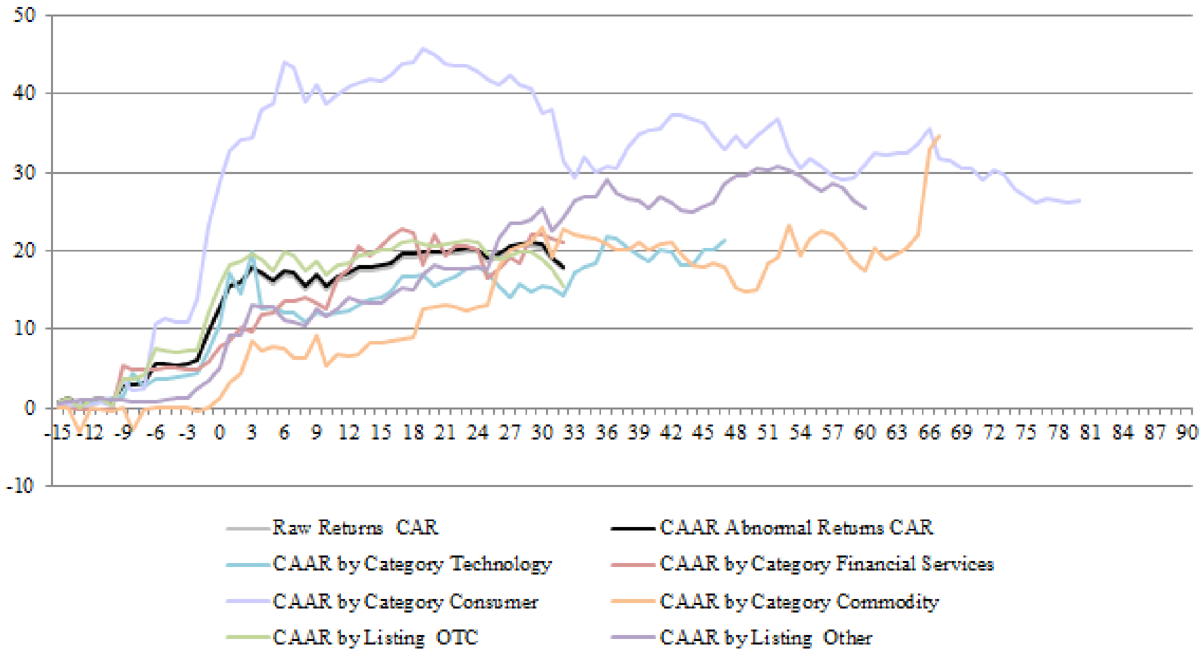
[34] Again, this result might be driven from statistical misspecifications outlined before under "Hypotheses".

[35] For the post-event windows (6) and (7), not a full cross-sectional sample of 18 observations is available due to the fact that some companies have changed their names in the very recent past, and consequently no +60 or even +90 post-event window can be provided. This is the case for 3 companies in the case of event window (6) and 7 companies in the case of (7). Consequently, the CAAR baskets cannot be drawn until the full +90 days time period. However, the arguments stated are fully reflected by the graph.

Figure III

Cumulative Abnormal Returns Earned Around the Announcement Date by Categories

Figure III graphically presents and confirms the results outlined in Table III. Figure III shows the evolution of various cross-sectional CAAR setups by continuously accumulating the abnormal returns staring from day -15 up until +90. Besides the various cross-sectional subsamples discussed under Table III, the raw returns CAR evolution is also added to this graphical representation. Note that, for the post-event windows (6) and (7), not a full cross-sectional sample of 18 observations is available due to the fact that some companies have changed their names in the very recent past, and consequently no +60 or even +90 post-event window can be provided. This is the case for 3 companies in the case of event window (6) and 7 companies in the case of (7). Consequently, the CAAR baskets cannot be drawn until the full +90 day time period. However, the arguments stated are fully reflected by the graph.



First, focusing on the difference of cumulative average raw returns and cumulative average abnormal returns (CAAR), a rather similar evolution can be observed. This is given due to the relatively small explanatory power of the market model in measuring abnormal returns. This, in turn, is more attributable to the fact of low capitalized and relatively illiquid individual stock returns rather than the wrong market index (i.e. the OTC Markets Index).[36] Hence, the market model shows limited ability to better explain the abnormal performance than simple raw returns and a constant mean return model.[37] The abnormal returns, on a cumulative level, even show a slight outperformance vis-à-vis to the raw returns. This is given due to the mostly

[36] Several other market indexes were tested in the context of the work at hand and all show similar statistical properties.
[37] Refer to "Limitations & Discussion" for an in-depth discussion on this matter.

(and on average) negative beta coefficients estimated for the individual sample companies and accordingly the positive return premium of market adjusted returns. Again, this fact is given due to the relative small capitalization and the associated contra cyclical developments of the OTC listed stocks.

Considering Table III, as well as Figure III, cross-sectional industry and listing differences in the cumulative abnormal performance can be observed. Picturing stock exchange listings first, higher CAARs among OTC listed sample firms can be observed closely around the event date relative to firms listed on other stock exchanges. While OTC listings record CAARS of 34 and 63 percent for event windows (2) and (3) respectively, other listed firms report 33 and 45 percent for the same windows respectively. Interestingly, for event window (2) the marginally higher (+1%) CAAR of the OTC listed firms is statistically highly significant, while for the other than OTC listed firms the CAAR is not statistically significant. In contrary to the expectation, this is due to the greater cross-sectional (and time-serial) abnormal return volatility of large capitalized firms (which tend to be other than OTC listed) and thus the decreased t-statistic. Considering the F-statistic between stock listings, however, no strong evidence for statistically significant differences in CAAR is provided for event windows closely around the event window (indicated by the p-value of 0.292 and 0.050 in event window (2) and (3) respectively). Thus, the *H5* of *CAARs not being significantly different among listing baskets closely around the event date* can be accepted.

Similar to the differences among listings, observing the CAARs among the different industries shows heterogeneous results. On the one hand, companies within the Consumer industry seem to profit most of the "blockchain effect", indicated by the highest CAARs closely around the event date (i.e. event window (2) and (3)) of 52 and 128 percent respectively. On the other hand, firms within the Financial Services and Commodity industry, although still positive, earn the least CAARs over event window (2) and (3) (14% and 29% for Financial Services as well as 18% and 24% for Commodity respectively). Although one might expect companies active in the Technology sector to earn the greatest abnormal returns (due to the actual involvement and revenue connection to the technology instead of the name change alone), with 55 and 58 percent for the event windows (2) and (3) respectively, the CAARs follow more or less the average cross sectional mean abnormal returns. However, in terms of statistical significance, the CAAR of firms active within Technology for an event window between -2 to +2 (i.e. event window (3)) indicates the highest significance with a t-statistic of 4.33. Considering the F-statistic, however, no evidence of significant differences among subsample CAARs closely around the event date is provided (indicated by the p-value of 0.316 in event window (3)). Thus, the *H4* of *CAARs of industry baskets not beeing significantly different among each other for event windows closely around the event date* can be accepted.

6.5. Potential Trading Strategies

The event study analysis also provides useful guidance on whether an event is suitable for a short-term trading strategy or not.[38] Whether or not the "blockchain effect" on average provides a suitable trading strategy, on the extend that an investor can identify in real time the announcements from the web sites in the Appendix I, depens on the CAAR following right after the event day (day zero). As such, on day +1 (i.e. the day right after the announcement of the blockchain name change), firms in the overall cross-sectional sample earn an average abnormal return of 15 percent, where OTC listed companies earn 12 percent and the rest of the sample 22 percent. According to the sample at hand, the highest day +1 returns can be earned using stocks within the Technology sector (+35%) and the least with stocks from the Financial Services sector (+4%). Also, day +2 abnormal returns, although less extensive indicate a short term profit potential with an average cross-sectional abnormal return of +2 percent. Thus, given the data at hand, the *H6* of *CAARs being positive in the days following the name change event and thus providing a short-term training strategy* can be accepted.

6.6 Robustness of the "Blockchain Effect"

The stated hypotheses regarding the robustness of the initial results are analyzed hereafter. That is, whether results are robust to outliers (*H7*), whether they are affected by market momentum (*H8*) or whether they are explained by shifts in investor sentiment (*H9*). The analyses are highly relevant as one is interested to what extend the "blockchain effect" can be considered sustainable.

[38] Note, however, that methods and results outlined here are particularly sensitive to the statistical assumptions underlying the event study methodology and the accurateness of the work performed.

6.6.1. Robustness to Outliers

A robustness analysis with a focus on outliers helps to explain whether the results are mainly driven by a few extreme market reactions or if they stem from a more fundamental underlying trend (i.e. consistent with the majority of sample observations). Table IV shows the CAARs calculated initially in this section but excluding the top 95th and the bottom 5th percentile of individual abnormal returns. That is, the most extreme 10 percent of time-serial abnormal returns from every individual sample observation are excluded in order to come up with the Mid90 abnormal returns calculated using the OTC Market Composite Index for the normal performance.

First, considering the calculated Mid90 abnormal return and t-statistics for the overall cross-sectional sample, the results seem quite robust relative to the unrestricted sample calculated in Table III. While the CAARs decreased in every event window except of (4) (where they increased from 14 to 20 percent by excluding the outliers), significance levels, although decreasing as well (again, except for event window (4)), show a similar picture. Event window (3)'s CAAR of 15 percent (compared to 58 with outliers) is still statistically significant on a 5% level (indicated by the t-statistic of 2.94). However, the two-day CAAR in event window (2) is not statistically significant anymore if outliers are excluded from the sample (t-statistic decreased from highly significant 3.26 with outliers to 1.10 without outliers) indicating limited robustness for the "blockchain effect" as well as increased volatility right at the event date and the day after.[39] Anyhow, the *H1* of *a firm's name change towards the blockchain technology being significantly associated with abnormal returns generated by virtue of the name-change announcement* is equally supported by the Mid90 data and is thus considered robust to outliers.

[39] Note that this F-statistic is not reported in either Table III or Table IV.

Table IV

OLS market model CAARs using only Mid90 abnormal returns calculated using the OTC Markets Composite Index

This table reports cumulative average abnormal returns (CAAR), excluding the 95th and the 5th percentile of time-serial abnormal returns, expressed in percent, and calculated using an OLS market model to derive normal performance. The underlying market index for the calculation of the market returns is the OTC Markets Composite Index. The CAARs are calculated using various event windows for companies that changed their names to blockchain names, between 12/31/2015 and 04/20/2018. Each cell reports the CAAR across all firms for the respective event windows. T-statistics are reported in parentheses. T-statistics significant at the five percent level are bold (i.e. t-statistic greater than 1.96). The CAARs are calculated for multiple sample subcategories, that is; industry specific subsamples (Panel B) divided into companies belonging to the sector Technology, Financial Services, Consumer, Commodity and all other undefined industries. Additionally, the sample is divided into stocks listed on OTC stock exchanges and the rest of the stock exchanges outlined under "data" (Panel C). P-values for tests of the null hypothesis of equality of means across firm categories using an F-test are reported at the end of Panel B and Panel C for the respective subsamples.

	Event Period						
	1	2	3	4	5	6	7
	-15 to -2	0 to 1	-2 to +2	+2 to +15	+1 to +30	+1 to +60*	+1 to +90*
CAARs according to OLS market model							
All (#18)	10 (1.04)	3 (1.10)	15 (**2.94**)	20 (1.83)	21 (1.03)	21 (0.80)	17 (0.67)
CAARs according to OLS market model by Industry							
Technology (#4)	17 (1.89)	-1 (0.13)	7 (0.70)	7 (0.73)	18 (1.25)	28 (1.89)	4 (0.51)
Financial Services (#3)	-2 (1.01)	3 (0.87)	8 (1.34)	27 (1.32)	63 (**2.31**)	46 (1.29)	50 (1.09)
Consumer (#4)	4 (0.54)	-6 (**2.41**)	12 (1.31)	49 (1.34)	18 (0.26)	42 (0.40)	50 (0.53)
Commodity (#3)	12 (1.15)	18 (1.78)	24 (**2.31**)	30 (**2.13**)	62 (1.21)	38 (1.11)	69 (1.78)
Other (#4)	19 (0.45)	7 (1.52)	21 (1.67)	-10 (0.88)	-34 (**2.39**)	-39 (**3.91**)	-58 (**3.50**)
F-test (p-value)	0.973	0.181	0.825	0.516	0.642	0.871$	0.609
CAARs according to OLS market model by Listing							
OTC Markets (#10)	9 (0.69)	2 (0.62)	12 (1.89)	24 (1.68)	12 (0.47)	13 (0.37)	9 (0.26)
Other (#8)	13 (1.52)	6 (1.38)	21 (**3.78**)	9 (0.83)	45 (1.42)	41 (1.88)	39 (1.32)
F-test (p-value)	0.059	0.305	0.152	0.107	0.406	0.052	0.168

*For the post-event windows (6) and (7), not a full cross-sectional sample of 18 observations is available due to the fact that some companies have changed their names in the very recent past, and consequently no +60 or even +90 post-event window can be provided. This is the case for 3 companies in the case of event window (6) and 7 companies in the case of (7). However, findings are assumed to stay unchanged. .

Second, the leakage and persistency profile of the "blockchain effect", for most of the event windows, stays the same after removing the outliers. CAARs in post-event windows in the overall cross-section are still positive and insignificant, that is; CAARs in percent (and their respective t-statistic) of 21 (1.03), 21 (0.80) and 17 (0.67) for event windows (5), (6) and (7) respectively. The same trend goes for the subsample of stock exchange listing specific companies. While in the original sample (i.e. with outliers) OTC listings where positive and insignificant, and other listings positive and partially significant (significant in event windows (6) and (7) with t-statistics of 2.34 and 2.02 respectively), now in the Mid90 sample both are positive but insignificant. In the industry subsample, however, by excluding outliers from the sample, companies active in Other industries show no persistent CAAR in the post-event windows, that is; negative (and significant) CAARs of -34 (2.39), -39 (3.91) and -58 (3.50) for event windows (5), (6) and (7) respectively. For the rest of the industry subsamples, however, Mid90 results for post-event windows stay consistent with the original results. Given those findings after excluding the outliers, the *H2* of *persistent CAARs over the post-event windows of up to +90 days following the event (day 0)* can also be generally accepted (although not all-encompassing due to the differences in Other industries) for the Mid90 sample. Considering pre-event windows, although still positive, no significant CAARs are generated by excluding outliers from the sample. Additionally, while stock active in the Technology sector are significant for event window (1) in the original sample (CAAR of 24 with t-statistic of 2.25), they are not anymore statistically significant after excluding outliers (CAAR of 17 with t-statistic of 1.89). Hence, the Mid90 results show even greater proof of the *H3* of *no statistically significant abnormal returns being observable over a pre-event window of -15 to -2 days prior to the event (day 0)* and thus do not indicate statistically significant leakage issues.

To conclude, the *H7* of *results being robust to outliers beyond the 95th and below the 5th percentile of individual time series returns* and consequently *of outliers not significantly changing the results regarding the "blockchain effect"* can, with a few minor exceptions outlined above, be generally accepted.

6.6.2. Momentum Effect

An explanation for the abnormal returns earned by the "blockchain effect" might simply be a momentum effect.[40] That is, stocks earning high abnormal returns prior to an event might also earn high returns after an event. By initially comparing event windows (1) and (4) (i.e. pre-event window returns from -15 to -2 and post-event returns from +2 to 15) given that both are positive in the overall cross-section, further analysis to fully conclude on a potential momentum issue are recommended.

To do so, a simple correlation check over the aggregated cross-section is performed. Average abnormal returns from -14 to 0 are compared to average abnormal returns from +1 to +15 by calculating the correlation coefficient. Given that the correlation coefficient is only 0.255 and, with a p-value of 0.360, insignificant, no momentum effect is assumed for the "blockchain effect". Thus, the *H8* of *pre-event market returns being uncorrelated to post-event stock returns and thus the CAARs not being a consequence of momentum* is accepted and abnormal returns in the context of a blockchain name change are considered robust to momentum.

6.6.3. Shifts in Investor Sentiment

When considering the original results in Table III, and being aware of the relationship between name changes and the BTC/USD currency exchange rate outlined introductory in Figure I, one might be interested whether the event study in the context of this "blockchain effect" are robust to different investor sentiments. In order to account for this issue, and to evaluate a potential managerial timing of such blockchain name changes, a brief analysis of investor sentiment is performed hereafter.

In order to examine whether blockchain name changes are robust across down an up market periods, monthly BTC/USD currency exchange returns (as a proxy for the investor sentiment in the context of the blockchain technology) are matched with the announcement month of the respective sample observation. Specifically, average monthly BTC/USD returns are first calculated during the period 12/01/2015 to 04/30/2015. After, the monthly BTC/USD returns are ranked into top-performing and bottom-performing month. Next, the sample observations

[40] Note that, for clarification, with the term „momentum" the individual firm specific momentum, rather than the market momentum, is analyzed.

are matched to their respective month of the event date (i.e. the announcement of the blockchain name change). Finally, in accordance with the previous results, the two different bins (sample size of 9 each) are separately analyzed on their CAAR performance over multiple event windows. This approach provides a straightforward way to account for investor sentiment and allows inference regarding the robustness of the original results on different blockchain market conditions. The following Table V provides an overview of the results obtained:

Table V

OLS market model CAARs from Top and Bottom monthly BTC/USD bins using the OTC Markets Composite Index

Table V reports cumulative average abnormal returns (CAAR), expressed in percent, and calculated using an OLS market model to derive normal performance. The underlying market index for the calculation of the market returns is the OTC Markets Composite Index. The CAARs are calculated for various event windows for companies that change their names to blockchain names, between 12/31/2015 and 04/20/2018. Each cell reports the CAAR across all firms for the respective event windows. T-statistics are reported in parentheses. T-statistics significant at the five percent level are bold (i.e. t-statistic greater than 1.96). The CAARs are calculated for two equally large sample subcategories in Panel B, that is; sample observations with an event date within the top-50%-month of monthly BTC/USD average currency returns (named Top BTC/USD) and sample observation with an event date within the bottom-50%-month of monthly BTC/USD average currency returns (named Bottom BTC/USD). P-values for tests of the null hypothesis of equality of means across firm categories using an F-test are reported at the end of Panel B and Panel C for the respective subsamples.

	Event Period						
	1	2	3	4	5	6	7
	-15 to -2	0 to 1	-2 to +2	+2 to +15	+1 to +30	+1 to +60*	+1 to +90*
Panel A: CAARs according to OLS market model							
All (#18)	33 (1.88)	34 (**3.26**)	58 (**3.37**)	14 (0.89)	44 (1.30)	34 (0.97)	39 (1.00)
Panel B: CAARs according to OLS market model by monthly BTC/USD bins							
Top BTC/USD	33 (1.34)	32 (1.71)	73 (**2.25**)	36 (1.91)	90 (1.56)	71 (1.16)	82 (1.19)
Bottom BTC/USD	39 (1.57)	42 (**5.55**)	48 (**4.21**)	-30 (1.08)	-22 (0.54)	-25 (0.66)	-29 (0.64)
F-test (p-value)	0.486	0.005	0.000	0.397	0.002	0.003	0.005

*For the post-event windows (6) and (7), not a full cross-sectional sample of 18 observations is available due to the fact that some companies have changed their names in the very recent past, and consequently no +60 or even +90 post-event window can be provided. This is the case for 3 companies in the case of event window (6) and 7 companies in the case of (7). However, findings are assumed to stay unchanged.

The average returns range from 0.17 percent (in June 2017) to 1.61 percent (in May 2017) for the top bin, and -1.28 percent (in March 2018) to 0.05 percent (in February 2018) for the bottom bin. The month with the most name changes is October 2017 (#4) (where a top bin monthly average BITC/USD return of 1.27% was earned).

According to Table V, the results do seem to be affected by positive market conditions. By considering the event window (3), closely surrounding the event date, the CAAR for the top BTC/USD increased to 73 percent from 58 percent in the original results. However, the significance decreased from 3.37 to 2.25 respectively. This also implies increased abnormal return volatility for companies announcing a blockchain name change within months of high average BTC/USD returns.[41] For the bottom-bin, on the other hand, considering again the event window (3), although the CAAR decreased relative to the original sample, the significance increased remarkably, indicating lower abnormal return volatility during low yielding BTC/USD month. Considering pre-and post-event windows, a remarkable difference to the overall cross-section are the negative CAARs for the bottom-bin within post-event windows ((4), (5), (6) and (7)). This result indicates a tendency towards only temporary "blockchain effect" for companies announcing a name change during a blockchain market downturn. However, as the negative CAARs are insignificant, the significant positive returns earned around the event date are still considered persistent. For the pre-event window, on the other hand, no differences between the bins are observable. This finding is also supported by considering the F-statistic of equal means across the two bins. While in the pre-evnet window the CAARs are insignificantly different from each other (p-value of 0.486), there is a statistically significant difference among CAARs for high and low performing BTC/USD-months in the post-event windows as well as the event windows closely surrounding the event date (e.g. p-value of 0.000, 0.002, 0.003 and 0.005 for event windows (3), (5), (6) and (7) respectively).

Thus, one can conclude that the *H9* of *CAARs significantly depending on investors' blockchain sentiments. Specifically, CAARs are expected to be significantly gather when the name change event happened during month with high BTC/UDS returns* can be accepted.

[41] Note that, the underlying reason might also be the actual high volatility of the BTC/USD currency exchange rate within the high yielding top-bin month instead of the high mean per se .

CHAPTER 7

DISCUSSION AND LIMITATIONS

The purpose of this chapter is to put the obtained results into perspective. On the one hand, statistical issues in the context of event study methodologies are analyzed and discussed in the context of the work at hand. On the other hand, economic issues for the blockchain name change valuation implications are elaborated and discussed.

7.1. Statistical Issues

Event studies are naturally based on a number of critical statistical assumptions in order to show a true and meaningful valuation effect of the respective event (Brown & Warner, 1985). Hereafter, the most important statistical issues in the context of the "blockchain effect" are touched up.

7.1.1. Normally Distributed Abnormal Returns and CAARs

When performing statistical inference in general, and particularly when using parametric tests, an assumption regarding the underlying distribution of the cross-sectional or time-serial data is required (Brooks, 2014). In the context of parametric event study testing regarding blockchain name changes at hand, the statistical analysis of Sections 4.3, 4.4, and 4.5 are based on the assumption of jointly normal and temporally independently and identically distributed (IID) abnormal returns (Campbell, et al., 1997). According to Brown & Warner (1985), departures from this assumption can lead to severe biases. They show, using multiple simulations, that without assuming normality, all results would be asymptotic and thus the normality assumption is essential for the exact finite sample results.

However, Brown & Warner (1985) as well as (1980) show that, generally, this assumption is not a problem. In their research on event studies using daily stock returns, Brown & Warner (1985) conclude the following regarding the non-normality issue: "The non-normality of daily returns has no obvious impact on event study methodologies. Although daily excess returns are also highly non-normal, there is evidence that the mean excess return in a cross-section of securities converges to normality as the number of sample securities increases. Standard parametric tests for significance of the mean excess return are well-specified. In samples of only 5 securities, and even when event days are clustered, the tests typically have the appropriate probability of Type I error[42]."

Hence, although the normality assumption is clearly violated, especially in the subsample cross-sectional representation of CAARs, these justifications from Brown & Warner (1985) as well as the early stated small sample properties of event studies from Jung (2006), the abnormal performance analysis in the context of a blockchain name change announcement in this work can be considered well specified and representative.

7.1.2. The Power of the Tests

In order to adequately interpret an event study, knowledge of the power of a test is inevitable (Campbell, et al., 1997). That is; the tests ability to detect the presence of a nonzero abnormal return and thus the likelihood that an event-study test rejects the null hypothesis for a given level of abnormal performance associated with an event.

Campbell, et al. (1997) performed various empirical simulations of abnormal performance using different statistical properties to find empirical patterns of test power. They showed that, using standard deviations of 2 and 4 percent (i.e. variances of 0.0004 and 0.0016)[43], that the power of the test increases (decreases) the lower (higher) the variance, the higher (lower) the sample size and, naturally, the greater (smaller) the abnormal returns. For example, they show that when the abnormal return is 2 percent the power of a 5 percent test with a sample size of 20 observations is 99 percent. Campbell, et al. (1997) equally conclude that, "generally, when the abnormal return is large one will have little difficulty rejecting the null hypothesis of no abnormal return". Additionally, Brown & Warner (1985) find that the results are robust to distributional assumptions, that is; that the analytical calculations and the empirical power are very close (i.e. if the distributional assumptions, such as a normal distribution in the case at hand, are inappropriate, the power computations are still accurate).

[42] I.e. the rejection of a true null hypothesis (Brooks, 2014).
[43] Which is, on average, in line with the sample properties underlying the „blockchain effect" in this work.

Given these findings our test results are considered to provide the required power to draw accurate statistical inference. Although the sample size is relatively small (with 18 observations in the overall cross-sectional sample and around 5 in the subsamples), the high abnormal returns in magnitude are assumed to account for high power in the empirical work at hand.

7.1.3. Non-Synchronous Trading

In accordance with Brown & Warner (1985) the use of daily data as a basis for a market model in event studies, especially when the market returns and security returns are each measured over a different trading interval, can lead to severe biases and inconsistency. However, Brown & Warner (1985) argue that, although beta estimates are downward biased in relatively infrequently traded shares and upward biased in relatively frequently traded shares, the biases do not necessarily imply misspecification in an event study. They argue that, by construction, the OLS residuals sum to zero in the estimation period and thus a bias in the beta coefficient is compensated for by a bias in the alpha coefficient. Also, Brown & Warner's (1985) simulations show that there is no improvement in the specification or the power when using other than OLS estimations such as Scholes & Williams' (1977) procedure.

Hence, although our data suffers from inconsistencies in the trading interval between market returns and security returns (as outlined earlier), the abnormal performance measures outlined under results are considered accurate. Equally, in accordance with Jain (1986), it is not beneficial to account for thin trading issues in the context of non-synchronous trading, event for firms with lower trading frequencies (such as, partially, the sample companies listed on the OTC Markets in the work at hand).

7.1.4. Bid-Ask Bounce in Daily Event Studies

In reference to Conrad & Kaul (1993), Campbell, et al. (1997) and Blume & Stambaugh (1983) an upward bias in CAARs can occur due to wide bid-ask spreads. According to Campbell, et al. (1997) the bias "arises from the observation-by-observation rebalancing to equal weights implicit in the calculation of the aggregate cumulative abnormal return combined with the use of transaction prices which can represent both the bid and the ask side of the market".

Given that for low capitalized firms, due to the relatively wider bid-asks spreads, the bias can be relevant (Conrad & Kaul, 1993), the on average relatively small capitalized sample companies in the context of the "blockchain effect" analysed in the work at hand might be affected by this issue. However, given that OTC listed firms show results contradicting this potential issue, it is assumed that the "blockchain effect" is robust to a microstructure-induced upward bias in returns. A possible remediation is considering CAR that represent buy-and-hold strategies (Campbell, et al., 1997).[44]

7.1.5. Increasing Volatility

Event induced volatility, and thus an underestimation of variance in the event study procedure, is a widely known and discussed issue (Boehmer, et al., 1991) (Brown & Warner, 1985). Boehmer, et al. (1991) investigate this issue by simulating an event with stochastic effects and find that "even when an event causes minor increases in variance, the most commonly-used methods reject the null hypotheses of zero average abnormal return too frequently when it is true".

In the case at hand, although variances for the generally small-capitalized sample are relatively high in the estimation window (and thus partially account for the induced variance by the event), this event induced variance poses a limitation for the empirical results. Due to the greater variance (induced by the event) than observed during the estimation window (using a market model), the statistical significance (i.e. t-statistics) might be upward biased.[45]

7.2. Economic Issues

Event studies are not only based on critical statistical assumptions, but also on assumptions regarding economic inference drawn from the results. The economic factors defined in the

[44] Note, however, that given the limited scope of the work at hand, this issue (and i.e. its remediation) is neglected for the blockchain name change event study at hand.
[45] Note, however, that given the substantial magnitude of abnormal performance, the statistical significance and the power is still considered representative.

model might be misleading for the true population, or subjective assumptions might not preserve in practice. This subchapter proavides some guidance and intuition about the economic assumptions stated for the “blockchain effect”.

7.2.1. Rationality of Investor Reactions

An inconclusive question remains whether the increase in firm value from a “blockchain effect” is rational, that is; stemming from investors fundamental expectation of potential future cash flows, or irrational in the dynamic of a speculative hype. However, the fact that results show that firms unrelated to the Technology sector earn similar abnormal returns as firms already involved in technological sectors, suggests at least partial investor irrationality. Also, Coopers, et al. (2001) argue that investors want to be associated with the technology “at any price”, implying rather unsustainable and irrational valuation. Hence, the results outlined provide insightful guidance to identify the value creation potential of the blockchain, however, due to suspected irrational and naïve investors’ behavior, the results should not be considered quantitatively flawless. Also, given that most of the sample firms are small and thus uncovered by the analyst community, investors might be unaware of the firms’ involvement with the blockchain technology. Then, once companies are switching their name to blockchain related names, investors realize the association with the technology and trade it at a premium. Huberman & Regev (2001) provide a good example of this sort of investors behavior. Naturally, this implies that markets are not semi-strong efficient (Coopers, et al., 2001).[46]

7.2.2. Long-Term Inference

Although post-event windows are considered in the work at hand (i.e. +2 to +15, +1 to +30, +1 to +60 and +1 to +90) no long-term inference about the valuation effect of a blockchain name change can be drawn (Rau, et al., 2002). Rather, the post-event windows present a short- to medium-term view of the markets assessment of the blockchain technology. Also, within those post-event windows, contaminating market reactions, although the obvious reactions are accounted for, dilute the abnormal performance associated with the blockchain

[46] It also implies that there might be a tendency of greater CAARs for companies already active in the technological industry (since now investors are aware of that). However, no such significant differences in abnormal returns can be observed in the results.

name change.[47;48] Refer to Conrad & Kaul (1993) for a closer discussion on long-term biases in computed returns.

7.2.3. Microstructure Issues

As a majority of the sample companies are traded on the OTC Markets, and thus given that most of the firms are rather small capitalized, it might be possible that the existence of any news positively affect the companies' valuation (Buckman, 1999). That is, the significant valuation premiums earned by a name change are less affected by the specific blockchain name change, but more by an action (i.e. news such as a name change) per se. However, given the substantial abnormal returns for OTC in accordance with other listed firms, this issue is considered as minor imporat for the events study at hand.

Due to the limited information available for the small capitalization stocks in the sample, no cross-sectional model to explain the CARs can be implemented unfortunately. This is because of the fact that firm specific characteristics such as size (i.e. market cap) or valuation (e.g. P/E ratio) are difficult or impossible to meaningfully obtain for OTC listed companies and small (and thus relatively illiquid) capitalized firms in general. Particularly the size effect (not only approximated by stock exchange listings) would be of notable interest in the context of blockchain analysis at hand, since due to the argumentations of short term investors focusing on small-cap stocks (because of the higher volatility and thus the greather return potential) the reactions are assumed larger for small companies.

7.2.4. Subjectivity

Note that several subjective economic elements were assumed throughout the event study of blockchain name changes. For instance, the OLS market model is assumed to best represent the true normal performance using the OTC Markets Composite Index as a market portfolio. The argumentation is that the majority of sample firms (13 out of 18) are listed on the index and that the index correlated will with larger-capitalized indices (such as the S&P 500). Also,

[47] For this reason, the results in the post-event windows should more serve for the analysis of the persistency profile of CAARs earned closely around the event date rather than taken literally.
[48] Also, the power of the statistical tests decreases dramatically with longer event windows. Refer to Brown & Warner (1985) for a simulation.

it is argued that since the stocks are relatively small capitalized and more illiquid than any index, the market model is likely to be the same regardless of which index is used. Nevertheless, note that results highly depend on the definition on normal performance. Finally, also the robustness tests depend heavily on subjective assumptions. For example, the assumption that average monthly BTC/USD currency exchange returns represent a well-defined measure for investors' sentiment towards the blockchain technology is highly subjective.

7.2.5. Geographical Limitation

Finally, the sample used at hand is not only focused on small-capitalized companies but also on companies listed (as well as operating) in the United States. Although sample companies from regions such as Israel or Hong Kong are included as well, the results are driven by the Anglo-Saxon countries. This fact, naturally, limits the ability to draw overall and conclusive inference about the markets valuation of the blockchain technology.

CHAPTER 8
CONCLUSION

To conclude, companies changing their name to a blockchain related name earn on average significant abnormal returns of 58 percent in the five days surrounding the event date. Also, in the short- to medium-term perspective, the effect does not seem to be transitory, as no significant negative post-event drift is observable. Thus, the assumption outlined in the introduction that the “blockchain effect” is comparable to the “dotcom effect” (Coopers, et al., 2001), experienced around the turn of the millennium, can be confirmed. Given that Coopers, et al. (2001) report “significant abnormal returns in the order of 53 percent” for the same event window, the market valuation for revolutionary technological changes appear to be similar. This also confirms that the blockchain technology is indeed comparable to the internet technology in terms of market valuation.

In terms of specific industry firm characteristics, no significant differences can be observed. Thus, as firms involved in the Technology sector earn only insignificantly different CAARs, the degree of evolvement in the blockchain technology prior to the name change does not seem to substantially affect market valuations. This conclusion supports the assumption that the results might be driven more by irrational investor mania than by a rational fundamental analysis from the investors’ side. Also, considering differences between OTC listed companies and firms listed on other stock exchanges as a proxy for a size effect, no significant differences can be observed. Overall, those findings indicate that the “blockchain effect” is stable across different firm characteristics.

Finally, it is found that market valuations of the blockchain technology are robust to outliers and the momentum effect, however, investors’ blockchain sentiments seem to influence the results. Companies changing their name within month of strong bitcoin acceleration earn significantly higher abnormal returns around the event date than firms announcing a name change in weaker bitcoin month.

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APPENDIX

Appendix I

Sources used to evaluate the "Blockchain Effect"

Appendix I provide an overview of the sources used in the work at hand.

Daily historical stock prices	https://www.yahoo.com/
	https://www.otcmarkets.com/
	Bloomberg
BTC/USD prices	Bloomberg
Daily market index prices	https://www.otcmarkets.com/
OTC listings	https://www.otcmarkets.com/
NASDAQ, NYSE, AMEX listings	https://www.nasdaq.com/
Other listings	Company web pages
Event announcements	https://www.ft.com/
	https://news.google.com/
	https://www.sec.gov/
Contaminating events	https://www.yahoo.com/ Bloomberg