Cross-listings: Cryptocurrency Characteristics and Abnormal Returns

MSc Financial Economics

Master Thesis

Student Name: **Reinout van Kampen**

Student Number: **466130**

Supervisor: **Dr. Dyaran Bansraj**

Second Assessor: **Dr. Jan Lemmen**

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Preface

I would like to thank my thesis supervisor, Dr. Dyaran Bansraj, for providing me clear feedback while considering my level of knowledge throughout the whole process. Your fast and clear responses as well as your flexible mindset have been most helpful. I also wish to thank Dr. Jan Lemmen for taking the role of second assessor.

Abstract

This study looks at 222 cross-listings of cryptocurrencies on 14 different exchanges for a time frame spanning from June 2018 to March 2020. A cross-listing is a positive event that creates awareness and allows more investors to participate. I therefore look at abnormal returns around the cross-listing date of cryptocurrencies. Although Ante (2019) and Benedetti and Nikbakht (2019) perform similar studies, not a single paper has tried to explain any abnormal returns around cross-listing from a cryptocurrency perspective. To do so I look at Bitcoin Dominance and the consensus mechanism of cryptocurrencies and relate these characteristics to cross-listing returns. I find significant cumulative average abnormal returns (CAARs) of 6.7% for the 7-day window (-3,+3) around the cross-listing. Abnormal returns are positive before- and on the announcement date, after which they become negative. Bitcoin Dominance, which represents the market share of Bitcoin relative to the entire cryptocurrency market capitalization, is negatively related to CAARs. I further test the three most common consensus mechanisms, Proof-of-Work, Proof-of-Stake, and Delegated-Proof-of-Stake and find that Proof-of-Stake cryptocurrencies obtain significantly higher CAARs than Proof-of-Work cryptocurrencies. These results contain important implications for investors and traders who want to know when to open or unload which cryptocurrency position. It also serves as an anchor for other researchers, interested in cryptocurrency characteristics, to build upon.

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1. Introduction

This paper studies the abnormal returns seen around the cross-listings of cryptocurrencies on centralized exchanges for the 2018-2020 timeframe. Cryptocurrency cross-listings are exchange listings of crypto's[1] that have already been listed before. To obtain a better understanding of what drives abnormal returns in the context of these cross-listings, several related variables will be tested. These include Bitcoin Dominance[2] and the consensus mechanism[3] of the cryptocurrency. The research question is therefore to explore drivers of abnormal returns with regards to the cross-listings of cryptocurrencies.

This paper aims to fill the research gap that currently exists in the cross-listing literature. Ante (2019) and Benedetti and Nikbakht (2019) demonstrate the existence of abnormal returns around cryptocurrency cross-listings, but do not aim to explain what drives these returns. Dharan and Ikenberry (1995) have done so but only for American stock cross-listings between 1962 and 1990. By looking at Bitcoin Dominance and consensus mechanisms, characteristics unique to cryptocurrencies, investors and traders will be able to make better estimates of when to buy or sell cryptocurrencies undergoing cross-listings.

A sample of 222 cross-listings between 2018 and 2020 is used in this event study. The cross-listings have been recorded by a Telegram bot (@CryptoExchangeListing). Data for independent- and control variables, as well as price data, has been retrieved from coingecko.com. After establishing the estimation- and event window, cumulative abnormal returns (CAARs) were calculated based on the Market Model of Brown and Warner (1985). Using this data, I have performed multiple t-tests over several event windows to examine the existence and size of CAARs around cryptocurrency cross-listings. I complemented these results by performing multiple ordinal least squares (OLS) regressions aiming to understand the impact of Bitcoin Dominance and the consensus mechanism on abnormal returns. I added several control variables, such as Market Capitalization and Trading Volume, as well as a one-way Anova and post-hoc test regarding the consensus mechanism variable for robustness purposes.

My results show that CAARs are 6.7% in the (-3,+3) event window around the cross-listing, significant at the 5% level. These findings are robust to other windows. CAARs are significantly positive on t-2, t-1, and t=0 as well as significantly negative on t+2. Abnormal returns become increasingly positive

[1] The terms, cryptocurrency, crypto's, and coins, will be used interchangeably throughout this paper.
[2] Bitcoin Dominance refers to the total cryptocurrency market capitalization represented by Bitcoin. It is expressed as a value between 0 and 100.
[3] The consensus mechanism of a cryptocurrency refers to the process of reaching agreement on the blockchain, for which many different mechanisms exist, each with their own properties.

before the listing and peak at the event date (t=0). The data also shows negative abnormal returns post-listing, indicating a short-term negative drift. Investors can use this information to strategically enter positions in cryptocurrencies anticipating a cross-listing or close existing positions at the right time. The best performance, based on this results of this paper, would be to enter a position at t-5 and close it at t=0, yielding a CAAR of 11.4%. The data also warns investors to be cautious chasing returns post-listing as they tend to be abnormally negative in the short-term.

After obtaining an understanding of how abnormal returns develop over time, I examined CAARs in relation to Bitcoin Dominance. CAARs are 0.7% lower for every percentage point increase of Bitcoin Dominance for the (-3,+3) window. This result, although only significant at the 10% level, has economical value as the difference between the highest- and lowest Bitcoin Dominance value was around 27 percentage points within the sample. Implying an expected difference of almost 20 percentage points in CAARs and even higher when adding control variables. This result is in line with hypothesis 1 which states that there is an inverse relationship between CAARs around cross-listings and Bitcoin Dominance. Investors could therefore take note of Bitcoin Dominance for trading strategies around cross-listings.

I then move on to research the relationship between the three most common consensus mechanisms in cryptocurrency and CAARs around cross-listings. CAARs are almost 13 percentage points lower for Proof-of-Work (PoW) coins than for the Proof-of-Stake (PoS) group, significant at the 10% level for the (-3,+3) event window. This effect is reduced to 8 percentage points after adding control variables. Delegated-Proof-of-Stake (DPoS) cryptocurrencies exhibit 3.5 percentage points lower CAARs than their PoS counterpart for the same event window although this is not statistically significant. The one-way Anova and post-hoc test, added for robustness purposes, verify this result and show that the overperformance of PoS cryptocurrencies is mainly due to a lack of negative abnormal returns post-listings. These results are in line with hypothesis 2a which states that PoS- experience higher CAARs than PoW cryptocurrencies. My findings do not support hypothesis 2b, which states that DPoS- experience higher CAARs than PoS cryptocurrencies around cross-listings.

This paper contributes to the scarce literature on cross-listings and verifies and complements the only existing papers on this topic Ante (2019) and Benedetti and Nikbakht (2019) by introducing predictor variables unique to cryptocurrency cross-listings. It has also broadened the scope of cross-listing papers, which is dominated by equity research. A third contribution is made to the literature on cryptocurrency returns. Although this paper does not test any specific strategies, it does relate

Bitcoin Dominance and consensus mechanisms to cross-listing performance and portrays the consequent implications for investors.

The remainder of this paper will proceed with the following chapters: Chapter 2 will review the literature on cryptocurrency cross-listings, Bitcoin Dominance, and Consensus mechanisms. Chapter 3 will outline the methodology of this event study. Chapter 4 will describe the sampling- and data collection process. Chapter 5 will report the analyses and corresponding results. Chapter 6 will provide the conclusion as well as any limitations and potential future research.

2. Literature Review

2.1 Background Information on Cryptocurrencies

Cryptocurrencies in their current form have been around since 2009 when Bitcoin was created by Satoshi Nakamoto, a pseudonym for an individual or group of people. The Bitcoin whitepaper, in which the technical fundamentals were laid out, was published a year earlier in 2008 (Nakamoto, 2008). The message encoded in the first ever Bitcoin block, "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks.", is widely interpreted as a criticism on the traditional financial industry. This can also be traced back to the protocol of Bitcoin. The fixed supply of 21 million is in stark contrast to the large-scale money printing of central banks.

In response to Bitcoin, many more cryptocurrencies followed and as of November 2021 there are more than 12.000 cryptocurrencies registered on coingecko.com (CoinGecko, 2021). Among these are multibillion cryptocurrency projects such as Ethereum, Cardano and Chainlink. The total Market Capitalization of cryptocurrencies has exceeded $3 trillion in November 2021 led by Bitcoin which effectively became the best performing asset of the last decade (Young, 2021).

Although many of these cryptocurrencies serve different purposes, they all use varying forms of blockchain technology. A blockchain is a ledger that records data, which is subsequently stored in blocks. These blocks are linked using cryptography, resulting in a chain of data. This concept enables blockchains to create trust as the records are distributed over a large network of computers rather than a centralized database and must be verified by multiple computers before being added to the blockchain. To tamper with the data, you would need to control more than half of the computers connected to the network (Sayeed and Marco-Gisbert, 2019), also known as nodes. Another characteristic of blockchain technology is that there is no need for intermediaries. All data stored on the blockchain has been verified and can therefore be trusted. Where cryptocurrencies generally make use of public blockchains, private blockchains can be used to limit access to certain users such as for the internal database of a firm (Hao et al., 2018).

Perhaps even more groundbreaking than the technology behind cryptocurrencies, is the price action seen since the emergence of Bitcoin in 2009. Like fiat currency, cryptocurrencies generally do not have any intrinsic value (García-Monleón, 2021). This makes it extremely hard if not impossible to value cryptocurrency. Similar to Metcalfe's law, the network size of the specific cryptocurrency could explain its value. This is confirmed by Liu and Tsyvinski (2021), who also find that investor attention and momentum possess significant explanatory power with regards to cryptocurrency returns. Kraaijeveld and De Smedt (2020) even demonstrate that investor attention in the form of Twitter sentiment can predict prices, although they admit it is extremely hard to prove which follows which.

2.2 Cryptocurrency Exchanges

The price data used in these studies is derived from the coingecko.com website, which is connected to numerous cryptocurrency exchanges through APIs to track the prices at which cryptocurrencies are being traded. Coingecko.com is tracking around 550 exchanges as of November 2021 (Coingecko, 2021). This list only records centralized exchanges such as Binance and Coinbase, indicating that there is a company that owns and facilitates the exchange platform and stores the cryptocurrency of their users for them. This is in contrast with decentralized exchanges where users remain in full control of their private keys and interact with the exchange through smart contracts. It was not possible to track decentralized exchanges due to data limitations. Trading Volume on decentralized exchanges grew exponentially in 2019 and 2020 (Shen, 2021) and started competing with their centralized counterparts.

Centralized exchanges have taken a pivotal intermediary role in the cryptocurrency ecosystem, connecting fiat- and cryptocurrencies. Total Trading Volume on these exchanges was around $250 billion in June 2021 and has seen enormous growth in the past years (Coingecko, 2021). Not only do these exchanges facilitate the purchasing and selling of cryptocurrencies, more and more features are being added such as savings, staking, and access to Initial Coin Offerings (ICOs) (Binance, 2021). Another major difference is that any cryptocurrency can be listed and traded on a decentralized exchange, whereas centralized exchanges are generally stricter on the cryptocurrencies being listed as only reputable projects with an extensive track record will be listed (Binance, 2017).

2.3 Cross-listings

Cross-listings are a phenomenon not unique to cryptocurrencies. A cross-listing generally refers to the listing of a financial asset after it has already been listed at least once. It therefore already has a market price in which it differs from a primary listing. With regards to cryptocurrencies, the first time a coin is listed is considered a primary or initial listing. Supply and demand will then decide the price which often happens with high levels of volatility in the first few days until the price settles and becomes more correlated to the rest of the market (Smales, 2020). This is different for cross-listings. Those involve cryptocurrencies that have already been listed on at least one exchange and are therefore already traded at market price. Cross-listings are often received with more anticipation by cryptocurrency traders as it includes cryptocurrencies that already have a track record and are more widely known. A cross-listing would therefore expose the to be listed asset to a larger audience which results in an anticipated increase in demand. It is therefore quite common to see a cryptocurrency go up in price after a major exchange has announced that it will be cross-listed. The so-called 'Coinbase Effect' refers to this phenomenon of a price increase following a cross-listing announcement of the Coinbase exchange (Dantes, 2021). This trend has been studied by the cryptocurrency analysis firm Messari and its result for six major exchanges on the cumulative 5-day performance is shown below. Coinbase has seen an average price return of 91% (Talamas, 2021).

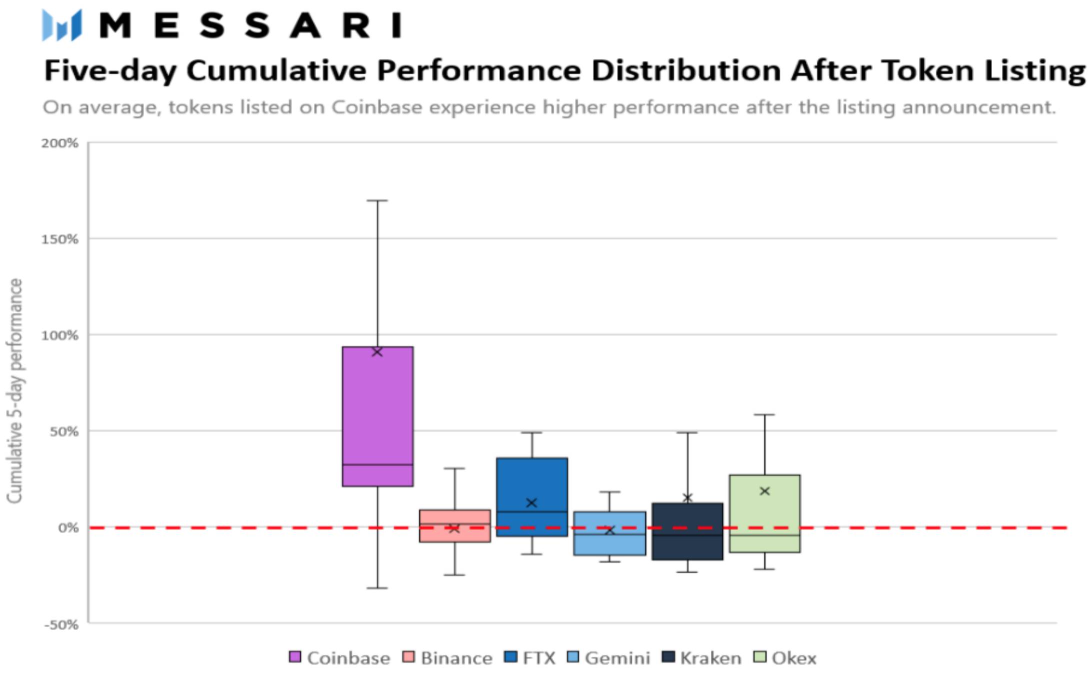

Figure 1: Cumulative 5-day performance for cryptocurrency listings on five major exchanges in 2021. Graph taken from Messari.io (2021).

The body of literature on cross-listings is heavily stock dominant. Most of the studies on this topic refer to the listing of a stock on a prime exchange (NYSE, NASDAQ) after it was already listed on a smaller exchange. The results have been mixed. Lau et al. (1994) do not find an effect on stock returns whereas Miller (1999) conclude a positive effect on stock prices. Dharan and Ikenberry (1995) find positive abnormal returns pre-listing, yet the opposite post-listing. The latter find support that companies knowingly have their stock cross-listed before a negative price event, in which information asymmetry is the main driver of this result.

Unlike stocks, cryptocurrencies do not have a say in when their project is cross-listed. The developers can therefore not time the listing and centralized exchanges aim to keep cross-listings a secret to avoid reputational damage. This is a material difference with stock cross-listings and is one reason to look at cryptocurrency cross-listings separately. Despite this key difference, Benedetti and Nikbakht (2019) find a similar price pattern for cryptocurrencies on the (-14,+14) window. Positive abnormal returns, followed by a price reversal post-listing. Ante (2019) looked at a shorter event window (-3,+3) and found a similar yet weaker effect. The former does not make any clear statements about a potential reason for this price development. The latter claims informed trading in anticipation of a cross-listing to be of significance. A case for information asymmetry due to timing, as seen in stock cross-listings, is unlikely given the randomness at which coins are cross-listed. Increased selling pressure due to profit taking and information leakage seems more likely.

2.5 Bitcoin Dominance

Ofek and Richardson (2003) find that growth stocks outperform value stocks during bull markets and vice versa during bear markets as investors increase (decrease) their risk appetite. This can be explained by value stocks having a larger Market Capitalization and lower volatility, whereas the opposite is true for growth stocks. Investors know this and aim for the highest returns depending on the market cycle. A similar event takes place in the cryptocurrency market, where investors rotate out of Bitcoin and into alternative coins (altcoins) or vice versa. This in turn impacts the Bitcoin Dominance value, a percentage indicating the market share of Bitcoin relative to the whole cryptocurrency market. Historical data from TradingView indeed shows that an increasing demand for altcoins leads to a decrease in Bitcoin Dominance. It also shows an inverse correlation between the overall cryptocurrency market cap and Bitcoin Dominance as investors rotate out of more speculative altcoins. Smales (2020) also note a decrease in correlation between Bitcoin and altcoins when Bitcoin Dominance decreases. It is therefore likely that the state of the market (bull/bear) also has an impact on abnormal returns around cross-listings. Bitcoin Dominance is therefore a proxy of the condition in which the cryptocurrency market finds itself and other than overall price performance is also likely to affect cross-listing performance. Therefore, based on the above findings, the following hypothesis about Bitcoin Dominance as a predictor of CAARs around cross-listings is formulated:

H1: *The lower Bitcoin Dominance is, the higher the CAARs around the cross-listings of cryptocurrencies.*

2.6 Cryptocurrency Consensus Mechanisms

The consensus mechanism is the process in which agreement between the participants on the blockchain of a cryptocurrency is reached. As there is no central database, transactions are verified multiple times by several different users before a block is added to the blockchain. There are numerous choices for which consensus mechanism can be used which has many implications for the price of a coin.

Bitcoin uses a Proof-of-Work (PoW) consensus mechanism and many other crypto's have followed this example, making it one of the most common occurrences. PoW cryptocurrencies must be mined using expensive- and energy consuming hardware. Rewards for this computing power come from newly issued coins and transaction fees, paid in the crypto that was mined. A positive price event, such as a cross-listing, is therefore likely to see increased selling pressure from miners who convert their coins into fiat currency to cover the earlier mentioned costs. This could increase selling pressure during the run-up or post event date and reduce the announcement return.

Another common consensus mechanism[4] is Proof-of-Stake (PoS). Rewards for these coins can be obtained by simply keeping a stake (share) of that crypto on the blockchain. The bigger the stake, the bigger the chance of validating the next block and receiving rewards. PoS users will therefore have an incentive to not sell their coins as this would decrease their chance of receiving more coins. A second mechanism in PoS cryptocurrencies that alleviates selling pressure are unstaking periods. These refer to a fixed amount of time a user must wait for their coins to become available after they choose to quit the staking process. This period varies per cryptocurrency but tends to vary from a few days to a few weeks. Selling your coins as soon as a positive price event takes place becomes therefore impossible. It is therefore expected that PoS cryptocurrencies see higher abnormal returns around their cross-listings.

A third common consensus mechanism is Delegated-Proof-of-Stake (DPoS). It is very similar to PoS. The main difference, however, is that holders can vote for governance proposals using their stake (Prayag, 2019), and generally have a larger voice in the development of the project (Cryptopedia, 2021). The incentive to hold on to their stake is therefore even bigger than for PoS. Selling pressure around cross-listings is therefore expected to be the lowest for this consensus mechanism.

There are no known reasons for buying pressure around cross-listings to be impacted by the consensus mechanism. Selling pressure, however, is expected to vary greatly based on the mentioned implications of all three consensus mechanisms. The following hypotheses about consensus mechanisms as a predictor of CAAR around cross-listings are formulated:

H2a*: The CAARs around the cross-listing of PoS cryptocurrencies is higher than for PoW cryptocurrencies.*
H2b: *The CAARs around the cross-listing of DPoS cryptocurrencies is higher than for PoS cryptocurrencies.*

[4] According to Hazari and Mahmoud (2019), 42% of the top 50 cryptocurrencies in December 2018 used PoW compared to 12% which used PoS. DPoS was used by 14%. The remaining 32% used a wide range of other consensus mechanisms.

3. Methodology

3.1 Event Study Methodology

Event studies are used to analyze (abnormal) returns for assets that undergo a specific event. The event in this paper refers to the cross-listing of cryptocurrencies. Abnormal returns must be calculated to find out whether these cross-listings can generate returns that beat the market and how they develop over time. I expect positive abnormal returns as cross-listings create awareness and allow more investors to participate thereby increasing demand and liquidity. As mentioned by Ante (2019), investors tied by capital control regulations (e.g. South-Korea) can only purchase cryptocurrencies from state-licensed exchanges. Short-term speculation is also likely to take place (Liu and Tsyvinski, 2021), which can drive prices up even further. Abnormal returns are likely to become negative post event, as proven by Benedetti and Nikbakht (2019), and potentially driven by selling pressure from early investors as well as information leakage.

1. The event study methodology used is based on Bowman (1983) and consists of five steps. The first step is the identification of the events. The relevant events for my sample have been recorded by a publicly available Telegram bot, called @CryptoExchangeListing, which has a connection to fourteen centralized exchanges. The bot mentioned the cryptocurrency as well as the date and exchange on which it took place. I identified all recordings and back tested the listings against information on the websites of the corresponding exchanges.

2. The second step consisted of calculating and modelling the price reactions. This was done for both the estimation- and event window. There is no perfect way to determine the length of the event window. M&A research often focuses on a (-3,+3) or (-5,+5) window, such as Becher (2000) does for banking mergers. Ante (2019) tests many event windows, but mainly focuses on the (-3,+3) window for further research. Benedetti and Nikbakht (2019) look at a longer event window (-14,+14). Krivin et al. (2003) mention that volatility is a good proxy for the true length of the event window. This is most in line with the (-3,+3) window (see *Figure 2*). This research will therefore build upon the (-3,+3) window for the hypothesis testing in addition to its widespread occurrence in academic research. Other windows such as (0,+3), (-1,+1), and (-5,+5) will be added for robustness purposes and to obtain an account of a potential price reversal in the days following the cross-listing. The period of (-3,-1) is when the general market does not know of the future listing, but information leakage could take place. Although this is not regulated in the cryptocurrency universe, exchanges will want to keep cross-listing dates as secret as possible to prevent reputational damage. It is therefore that the (-3,-1) window could provide interesting information.

The estimation window has been set at (-30,-10). This deviates from traditional finance research where a longer period is the norm. Dyckman et al. (1984) advise a 60-day (-120,-60) period for event studies, whereas Capron and Pistre (2002) use a double 130-day window (-180,-50 / +50,+180) for their study on acquisitions. My 21-day period is equal to Ante (2019) and can be justified for multiple reasons. Cryptocurrencies are cross-listed continuously on different exchanges. Lengthening the estimation window would capture cross-listings of the same asset on other exchanges. As seen in the *Data* chapter, 89 listings could not be used due to an overlap in the event- or estimation window. A longer estimation window would increase this overlap even more and reduce the sample size significantly. A longer estimation window might increase the accuracy of the abnormal returns calculated later, but also increases the probability of capturing other events than cross-listings. Adding a longer estimation window for robustness purposes would be ideal but unfeasible due to data limitations.

3. I calculate the abnormal returns after having obtained all the relevant price reactions in the right time frame. The market returns during the estimation period were used to calculate any abnormal returns, based on the Market Model (Brown and Warner, 1985). The Constant Mean Return Model, often seen in event studies, is less useful as it does not incorporate Bitcoin. The cryptocurrency used for exchanging between coins. Altcoins are often bought with Bitcoin, to outperform Bitcoin. This is similar to stock-picking to generate higher returns than the corresponding index. The notion of using Bitcoin as a market proxy is therefore obvious and in accordance with most cryptocurrency related papers such as Liu and Tsyvinski (2021). There is currently no generally accepted market index of cryptocurrencies such as the S&P 500 or MSCI World index for stocks. Choosing one would therefore be arbitrary and extremely tedious due to the ever-changing rankings of cryptocurrencies. Based on these arguments Bitcoin is chosen to be the sole market proxy and is used to calculate abnormal returns in the identified cross-listings.

The Market Model expected returns will therefore be calculated over the estimation window as:

$$R_{i,t} = a_i + b_i R_{BTC} + e_{i,t}$$

Abnormal returns (AR) will be calculated as:

$$AR_{i,t} = R_{i,t} - b_i R_{BTC}$$

4. Cumulative Abnormal Returns (CARs) are then achieved by summing up AR across the event window. Finally, Cumulative Average Abnormal Returns (CAARs) are obtained by averaging across all 222 cross-listings in the sample.

5. The results will be analyzed to see whether abnormal returns are indeed present and to which extent. Different event windows will be compared to each other as well as to other studies. Significance will be tested by calculating a parametric t-test.

3.2 Bitcoin Dominance Methodology

Bitcoin Dominance refers to the proportion of the total cryptocurrency Market Capitalization that consists of Bitcoin. There is no universal benchmark for what constitutes as high or low Bitcoin Dominance. This percentage, however, has shown a descending trend over the years, given the rise of many altcoins.

The research on this topic, however, is scarce to non-existent. Peterson (2019) has done some investigations, but his measures only compare Bitcoin- to Bitcoin Cash dominance (a hard fork of Bitcoin). It is therefore that two new measures will be used to test hypothesis 1.

The first measure treats Bitcoin Dominance as a scale variable. This measure will aim to test if a higher Bitcoin Dominance is correlated to higher abnormal returns around cross-listings. It will give the most detailed information and can be applied to other periods outside the sample as well. Even when Bitcoin Dominance is significantly higher or lower.

The second measure treats Bitcoin Dominance as a nominal dummy variable which can take a value of 0 (low) or 1 (high). These values are assigned based on whether Bitcoin Dominance is below or above the sample median of 58.88 on the listing day (see *table 1*). Bitcoin Dominance shows an upward trend during the sample over time but rises above and below the median four times (see *Appendix B*). Every year over which the sample is taken does therefore contain below- and above median values.

Both variables will be used in an OLS regression of CAARs to test the correlation and implied impact on the abnormal returns around the corresponding cross-listings. The event-window will be (-3,+3). Control variables such as the exchange, Trading Volume, Market Capitalization, and year will be used for robustness purposes.

3.3 Consensus Mechanism Methodology

Hypothesis 2a and 2b relate to the verification process of cryptocurrency transactions, the consensus mechanism. The measure chosen will treat the consensus mechanism variable as a categorical variable that can take three values. Proof-of-Stake (PoS), Delegated-Proof-of-Stake (DPoS), or Proof-of-Work (PoW), together responsible for 68% of all cryptocurrencies' consensus mechanisms in 2018 (Hazari and Mahmoud, 2019). There is not a fourth common mechanism that is as commonly shared among cryptocurrencies and the remaining coins in the sample use a large variation of almost all unique mechanisms. Although it is possible to create a fourth value that represent all cryptocurrencies with another consensus mechanism, no possible explanation in relation to any abnormal returns around cross-listings would be possible as this group would not share any characteristics among the corresponding events. Only the earlier mentioned three options will therefore be used. The measure will aim to test hypothesis 2a and 2b and discover whether consensus mechanisms are a significant predictor for abnormal returns seen in cross-listings.

The variables will be used in an OLS regression of CAARs, similar to Bitcoin Dominance for the (-3,+3) event window and will be run as three individual dummies. The same control variables will be added. Given that the independent variable (Consensus mechanism) in this hypothesis is categorical and the dependent variable (CAARs) is interval, a one-way ANOVA and a potential post-hoc Tukey HSD test will be used to perform a robustness test.

3.4 Control Variable Methodology[5]

3.4.1 Exchange

The first control variable relates to the exchange on which the cryptocurrency was listed. The sample includes listings from fourteen exchanges. Bigger exchanges such as Binance and Coinbase will have a larger customer base and more marketing power than smaller exchanges. This effect will be captured by adding exchange dummies to the regression.

3.4.2 Year

The second control variables refer to the time and corresponding market circumstances at which the listing took place. Whereas Bitcoin Dominance is meant to account for cryptocurrency related market sentiment, this variable will account for general market conditions that fluctuate over time. Cross-listings in the sample come from 2018, 2019, or 2020. The effect will be captured by adding year dummies to the regression.

3.4.3 Trading Volume

Other than the exchange and year corresponding to the cryptocurrency, its Trading Volume will be used as a third control variable. This is an important variable as higher trading volume will lead to increased liquidity. Foster and Viswanathan (1993) have shown that trading volume and volatility are positively correlated which could have a profound influence on the returns found in cross-listings.

[5] Unfortunately, it was not possible to control for the number of times a specific cryptocurrency had already been listed due to data limitations.

The Trading Volume variable will be measured as the cryptocurrency's overall average trading volume in USD along the estimation period. This is done to prevent capturing part of the volatility due to the cross-listing. Exchange specific data was unavailable. I use logarithmic transformation for statistical purposes to remove excessive skewness given the wide range of observations and significant outliers in both directions as well. The following formula is used:

$$Trading\ Vol = \log\left(\frac{\sum_{t-30}^{t-10} Trading\ Vol}{21}\right)$$

3.4.4 Market Capitalization

Similar to Trading Volume, the market capitalization of a cryptocurrency can help explain any abnormal returns seen in cross-listings. It is obvious that, if liquidity is constant, it will require more capital to drive up the price of an asset that has a higher market cap and vice versa. Fama and French (2021) mention that market capitalization plays an important role in explaining stock returns, with smaller stocks having higher expected returns. It would therefore be interesting to see whether a similar small stock premium also exists for cryptocurrencies cross-listings.

The Market Capitalization variable will be measured as the cryptocurrency's overall average market capitalization in USD along the estimation period. This is done to prevent capturing part of the volatility due to the cross-listing. Exchange specific data was unavailable. I use logarithmic transformation for the same reason as for Trading Volume. The following formula is used:

$$Market\ Cap = \log\left(\frac{\sum_{t-30}^{t-10} Market\ Cap}{21}\right)$$

4. Data

4.1 Data Collection and Sampling

The events have been obtained through a publicly available Telegram bot, called @CryptoExchangeListing, which receives its data from numerous major exchanges through API connections. Most of the cryptocurrency related papers discussed in the *Literature Review* rely on websites such as coinmarketcap.com, coingecko.com or cryptocompare.com for price-, volume, or other data. These websites are connected to almost all centralized exchanges through APIs and can therefore generate several live metrics such as open- and close prices. Coingecko.com has been this paper's choice given its abundance of historical prices as well as outstanding accessibility. The price data needed for the cross-listings has therefore been obtained from this website.

The first listing reported was on 6 June 2018 and the last on 19 March 2020. Listings reported before and after these dates were updated on a weekly- rather than daily basis by the Telegram bot and could therefore not be used. This was discovered by manually fact-checking all listings through the corresponding exchange website. Only centralized exchange listings were used. Primary listings have been taken out of the sample as well as any cryptocurrencies with insufficient available price data. Stablecoin listings, which are cryptocurrencies that have their value pegged to fiat currencies, have been removed as well due to a lack of volatility. The same applied to derivative products of already listed cryptocurrencies. Listings in a period which estimation- or event window overlapped with a cross-listing of the same cryptocurrency were also removed. Using these would lead to distorted results as the estimation window of 21 days could become heavily skewed due to a cross-listing taking place in that period. Finally, any listings with insufficient available price data could not be used. This led to a remaining 496 useable listings (see *Appendix A*), which effectively reduces the sample size to 222.[6]

The sample set characteristics, include the date of the cross-listings, the (centralized) exchanges, and the required data availability on coingecko.com. It is therefore that, strictly speaking, the sample is representative for a population of cryptocurrencies that have been listed between 6 June 2018 and 19 March 2020 on one of the 14 centralized exchanges and have been tracked by coingecko.com. A point can be made however, that the sample set is representative for a larger population.

[6] Based on Israel (1992), a sample size of 221.4 would be appropriate, given a sampling frame of 500. This is rounded up to 222 to arrive at a sampling error of ±5% and a 95% confidence level (see *Appendix A*), as is recommended by Krejcie and Morgan (1970). The method used is a simple random sample.

4.2 Bitcoin Dominance Data

This data is directly recorded by Tradingview and is expressed as a number between 0 and 100. This number is calculated by comparing the Bitcoin Market Capitalization against the entire cryptocurrency Market Capitalization. It is obtained for the entire duration of the sample, covering the first (25-6-2018) to the last cross-listing (19-3-2020). As seen in *table* 1 below, the highest and lowest Bitcoin Dominance values during this period were 72.2 and 44.9 respectively, indicating the volatile nature of Bitcoin Dominance with a range of 27.3. The average was 60.5. This means that during the timeframe of the sample, on average, Bitcoin's value made up 60.5% of the entire cryptocurrency market.

Table 1. Summary statistics for *Bitcoin Dominance*.

N	222
Mean	60.49
Median	58.88
Standard Error	0.46
Standard Deviation	6.80
Minimum	44.87
Maximum	72.18

Table 2. Summary statistics for *Consensus Mechanism*.

N	222
No native consensus mechanism	59
Different consensus mechanism	64
Sample	99
Proof-of-Work	22
Proof-of-Stake	49
Delegated-Proof-of-Stake	28

4.3 Consensus Mechanism Data

To retrieve the consensus mechanisms of all 222 cross-listings, the cryptocurrency research website messari.io was used from which the data could manually be read off for every coin. Any missing records were complemented by downloading the corresponding whitepaper of that cryptocurrency. 64 cross-listings consisted of coins that did not have their own native consensus mechanism and relied on another cryptocurrency blockchain for the verification of their transactions. 59 cryptocurrencies used another consensus mechanism than the three most common mechanisms. Of the remaining 99 cross-listings, 49 used PoS, 28 DPoS, and 22 PoW (see *table 2*). This is a lot less than the initial sample set of 222, which makes the results more prone to outliers. To not exclude outliers and decrease the sample size even further, 95% windsorization is implemented for the corresponding CAARs.

4.4 Control Variable Data

The data for the control variables Trading Volume and Market Capitalization have been manually retrieved through coingecko.com for every cross-listing and logarithmically transformed (see

Methodology). Trading Volume appears to be more concentrated than Market Capitalization given the difference in the standard deviation. The lower count for especially Market Capitalization is due to missing data for some cryptocurrencies. The data for the Exchange and Year control dummy variables were readily available, as it was mentioned by the Telegram bot. Not many insights can be gained from their values given their categorical nature. *Table 3* below outlines the summary statistics for all control variables. *Appendix B* shows a more detailed overview of all variables.

Table 3. Summary statistics for all control variables.

Variable	**N**	**Mean**	**Median**	**SD**	**Min**	**Max**
Trading Volume (log)	214	6.17	6.23	0.07	3.79	9.48
Market Cap (log)	174	7.51	7.39	0.82	5.47	9.71
Exchange (dummy)	222	-	-	-	-	-
Year (dummy)	222	-	2019	-	-	-

5. Results

5.1 Overall Results

Table 4 below illustrates the CAAR for the (-3,+3) event window as well as several others, which is visually displayed in *Figure 2.* T-statistics as well as the proportion of positive (C)AAR across all events are provided.

Table 4. CAARs of 222 cross-listings around the event window. Multiple intervals are shown other than (-3,3) for robustness purposes. The Market Model is used with Bitcoin as a reference market.

Event Window	CAAR	t-statistic	% positive
(-3,+3)	**0.067**	**2.259****	**0.53**
(-5,+5)	0.071	1.815*	0.55
(-1,+1)	0.060	3.013***	0.48
(-3,-1)	0.046	2.670***	0.55
(0,+3)	0.021	0.931	0.53
-3	0.010	1.284	0.50
-2	0.018	2.454**	0.52
-1	0.018	1.738*	0.52
0	0.052	3.249***	0.57
+1	-0.010	-1.208	0.39
+2	-0.018	-1.892*	0.35
+3	-0.003	-0.430	0.43

*, **, *** indicates significance at the 10%, 5%, and 1% level respectively for a two-tailed T-test.

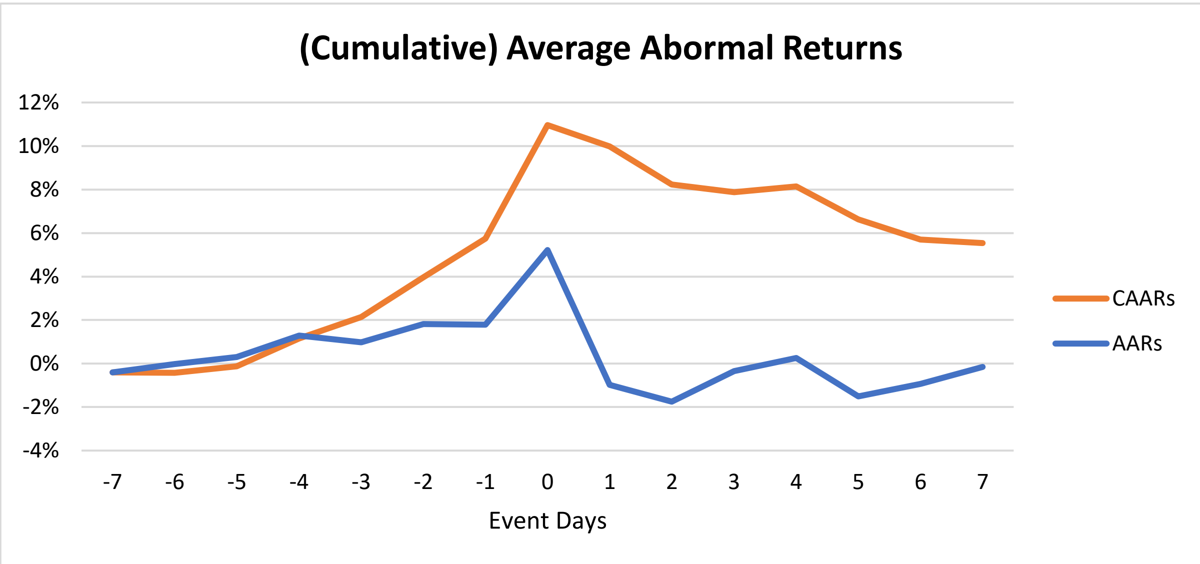

Figure 2: Average abnormal returns in blue vs. cumulative average abnormal returns in orange.

The CAAR of the (-3,+3) event window is 6.7%[7], which is significant at the 5% level. The (-5,+5) and (-1,+1) event window show a CAAR of 7.1% and 6% respectively, although the former is less significant. This confirms the existence of CAARs around the cross-listings of cryptocurrencies, which was expected as cross-listings create awareness and allow more investors to take part. Positive abnormal returns start five days before- and peak at the announcement date, yielding a CAAR of 11.4%. After this date a reversal takes place and at (+7) CAARs have decreased to 5.5%. This shows to investors that opening positions in cryptocurrencies anticipating a cross-listing can be rewarding if gains are materialized on time. My results suggest the announcement date to be the optimal day to close any positions.

The (-3,-1) window captures the time right before the general market becomes aware of the cross-listing. It shows a CAAR of 4.6%, significant at the 1% level. This shows potential information leakage and could help explain the reverse pattern seen post-listing, as informed traders unwind their positions. All three days after the event date show a negative CAAR as well as a lower proportion of positive AARs. This could indicate profit taking although it is not statistically significant and can therefore not be concluded.

The CAAR of 6.7% for the (-3,+3) window is lower than Ante (2019), who obtained a 9.2% CAAR. This could be explained by the difference in timeframe. Ante (2019) uses data from April 2017 to June 2019 while this paper has collected data from June 2018 to March 2020. The former captured the great bull run of 2017 whereas the latter saw cryptocurrency prices decline. The event date itself shows the highest CAAR (5.2%) of all individual days and is also the most significant. This is in line with Ante (2019) who finds a CAAR of 5.7%. When looking at traditional corporate finance papers, similarities exist although making comparisons is difficult. Ritter and Welch (2002) find an average first-day return of 18.8% in their study on IPOs. Much higher than my obtained 5.2%. This is not market-adjusted however and indicates a first (primary) listing. The results Dharan and Ikenberry (1995) have found are more in line with cross-listings. They look at already publicly traded stocks that move to the New-York Stock Exchange and find positive abnormal returns before listing and the reverse post-listing. Although similar to my results, a longer timeframe is needed for confirmation.

[7] It implies that the cross-listings in the sample yielded 6.7% CAARs. This is an economically significant result as Bitcoin (the reference market) has only seen a 7-day yield of 0.15% on average during the timeframe of the sample. Using the same metric for the MSCI World Index would yield 0.01%.

5.2 Bitcoin Dominance Results

Table 5. OLS regressions of Bitcoin Dominance (independent variable) and CAARs (dependent variable) around the (-3,+3) event window. Bitcoin Dominance is tested, both as a scale variable and dummy variable. Market Capitalization and Trading Volume are added as control variables as well as exchange- and year dummies and consensus mechanism dummies in model 5.

Regression	(1)	(2)	(3)	(4)	(5)[8]
Bitcoin Dominance[9]	-0.007* (0.0041)		-0.007* (0.0042)		-0.013* (0.0069)
Bitcoin Dominance Dummy		-0.083 (0.0586)		-0.046 (0.0622)	
Market Capitalization			-0.049 (0.0469)	-0.033 (0.0464)	-0.026 (0.0526)
Trading Volume			0.001 (0.0410)	-0.013 (0.0424)	-0.021 (0.0523)
Exchange-dummies	No	No	Yes	Yes	Yes
Year-dummies	No	No	Yes	Yes	Yes
Consensus mechanism-dummies	No	No	No	No	Yes
N	222	222	174	174	85
R-squared	0.011	0.009	0.082	0.064	0.087

*, **, *** indicates significance at the 10%, 5%, and 1% level respectively. Heteroskedasticity-robust standard errors can be found in parentheses[10].

Bitcoin Dominance is measured as a scale variable in models 1, 3 and 5 and as a nominal dummy variable in models 2 and 4. Control variables are included in models 3, 4 and 5. The number of observations is lower for these models due to missing data regarding Market Capitalization and a smaller sample size regarding the consensus mechanism.

[8] Model 5, which include Consensus mechanism dummies, has been added to prevent omitted variable bias. This reduces the sample size to 85, however, making its results considerably less reliable.
[9] I have chosen to not use logarithmic transformation for Bitcoin Dominance as it does not deviate from normality and has values of -0.77 and -0.13 for kurtosis and skewness respectively.
[10] Heteroskedasticity-robust standard errors have been calculated as described by Hayes and Cai (2007) for OLS regressions.

Model 1 shows a negative correlation between Bitcoin Dominance and CAARs, indicating that an increase in Bitcoin Dominance of 1 would lead to a decrease of CAARs of 0.7% for the (-3,+3) event window[11]. Although in line with hypothesis 1, it is only statistically significant at the 10% level. Model 2 shows that CAARs are on average 0.083 lower when Bitcoin Dominance is high compared to when it is low. This result, however, is statistically insignificant. Bitcoin Dominance remains unchanged after controlling for Market Capitalization and Trading Volume in model 3. The former has a coefficient of -0.049. Increasing Market Capitalization by 10% would therefore lead to a decrease of CAARs of 0.47%[12]. Neither control variables are statistically significant.

Models 3 also displays exchange- and year dummies. The former aims to control for the exchange on which the cross-listing took place, whereas the latter controls for the general market environment. This is important as some exchanges differ in size and trading volume which ultimately could affect any abnormal returns seen in cross-listing. Model 4 looks at the same variables with Bitcoin Dominance as a dummy variable. This reduces its coefficient to -0.046, albeit statically insignificant.

The results from these regressions are therefore in line with hypothesis 1, which states that there is an inverse correlation between Bitcoin Dominance an CAARs. This correlation is significant at the 10% level. As Bitcoin Dominance was used as a market proxy, more favorable market conditions in the form of lower Bitcoin Dominance seem to be positively related to CAARs.

[11] This correlation would have a large impact given the coefficient size. Bitcoin Dominance has shown a difference of 27 percentage points during the timeframe in which the sample was collected. This would result in CAAR being 18.9% (27×0.007) higher or lower in the (-3,+3) window. This is a considerate number as CAAR is 6.7% for the same window.

[12] The variables Market Capitalization and Trading Volume have been logarithmically transformed to reduce skewness. An increase of 10% regarding Market Capitalization in model 3 will affect the dependent variable as follows: $\beta \times \log(1.10) = -0.027 \times \log(1.1) \approx -0.0047$.

5.3 Consensus Mechanism Results

Table 6. OLS regressions of Consensus mechanism (independent variable) and CAARs (dependent variable) around the (-3,+3) event window. Consensus mechanism is tested as a categorical dummy variable. The reference group (Proof-of-Stake) has been omitted[13]. The same control variables as in *table 5* have been added.

Regression	(1)	(2)
Proof-of-Work (PoW)	-0.128*	-0.083*
	(0.0701)	(0.2534)
Delegated-Proof-of-Work (DPoS)	-0.035	-0.031
	(0.0513)	(0.2251)
Bitcoin Dominance		-0.013*
		(0.0069)
Market Capitalization		-0.026
		(0.0526)
Trading Volume		-0.0208
		(0.0523)
Exchange-dummies	No	Yes
Year-dummies	No	Yes
N	99	85
R-squared	0.0076	0.0649

*, **, *** indicates significance at the 10%, 5%, and 1% level respectively. Heteroskedasticity-robust standard errors can be found in parentheses.

PoS cryptocurrencies being the omitted dummy variable, CAARs for PoW cryptocurrencies are 0.128 lower for the (-3,+3) window in model 1[14]. This is only significant at the 10% level but is in line with hypothesis 2a. Whether this is caused by the selling pressure coming from PoW holders or lack of selling pressure (due to unstaking periods) from PoS holders cannot be concluded. CAARs for DPoS cryptocurrencies are 0.035 lower. This does not seem to be in line with hypothesis 2b but the coefficient is not statistically significant either.

Model 2 includes the same control variables as used for hypothesis 1. Bitcoin Dominance has been added for robustness purposes and is significant at the 10% level. The sample size for model 2 is

[13] Hypothesis 2a tests whether CAARs are higher for PoS than PoW. Hypothsis 2b tests whether CAARs are higher for DPoS than for PoS. PoS cryptocurrencies have therefore been set as reference group as they are referred to in both hypotheses.

[14] CAARs for PoS coins being 0.128 higher than for PoW coins is an economically significant difference. Investors and traders can use this information when choosing between cryptocurrencies anticipating a cross-listing.

smaller due to data limitations for Market Capitalization. This could have been solved by adding a fourth level to the Consensus mechanism variable, but this group would consist of cryptocurrencies without a native blockchain or with another consensus mechanism than PoW, PoS, or DPoS. Comparison would therefore have no economic meaning.

5.4 Robustness Check for Consensus Mechanism

To obtain more insights into the development of CAARs across the three Consensus mechanism groups, the following one-way Anova is used.

Table 7. One-way Anova of CAARs and Consensus Mechanisms. PoW, PoS, and DPoS make up the three groups. The F-statistic, p-value as well as means and standard deviations are presented in the table below.

			PoW		PoS		DPoS	
One-way Anova	*F*(2, 96-98)	*p*	*M*	*SD*	*M*	*SD*	*M*	*SD*
(-3,+3)	1.873	0.159	-0.0438	0.272	0.0943	0.501	0.0490	0.183
(-1,+1)	3.192	0.045	-0.0363	0.185	0.1094	0.272	0.0547	0.150
(-5,+5)	3.133	0.048	-0.1063	0.348	0.1175	0.395	0.0057	0.274
n	99		22		49		28	

Given the categorical nature of the independent variable and the dependent variable being a scale variable, a one-way Anova is used in addition to the regression in *table 6*. The groups are heterogenous in size. This is not a problem given the fact that the variances do not significantly differ (see *Appendix C*). One-way Anova is therefore still a robust method (Keppel, 1992).

The main event window (-3,+3) shows that the PoS mean indeed is higher than PoW (0.0943 > 0.0438), but not lower than DPoS (0.0490 < 0.0943). This Anova, however, is not significant (p=0.14). This indicates that there are no statistically significant differences between the group means. This is different for the (-1,+1) and (-5,+5) windows which are both significant at the 5% level. Post-hoc testing is therefore necessary to find out which means differ significantly. This is done through a Tukey HSD test.

Table 8. Tukey HSD analysis, showing only significant mean differences for the (-1,+1) and (-5,+5) window.

CAARs	Consensus Mechanism	*p*	Mean Difference	SE
(-1,+1)	PoW - PoS	0.035	-0.1457	0.058
(-5,+5)	PoW - PoS	0.043	-0.2238	0.091

The PoW and PoS are the only pairs that differ significantly. PoS cryptocurrencies have higher CAARs than PoW cryptocurrencies and this effect is the strongest for the (-5,+5) window[15]. The price reversal seen in *figure 2*, is also clearly visible in *table 7* for the PoW and DPoS groups. Both have the lowest CAARs for the (-5,+5) window. The opposite is true for the PoS group. This could be due to the unstaking periods that temporarily prevent PoS cryptocurrency holders from selling, effectively reducing selling pressure compared to the PoW group. It is unclear why this effect is not visible for the DPoS group. No claims, however, can be made about this group as it does not differ significantly.

[15] This result, which indicates the outperformance of PoS- over PoW cryptocurrencies around the cross-listing, is statistically significant and relevant for investors. The difference in CAARs is between 14% and 22%. PoS cryptocurrencies also do not see a reversal in CAARs within the (-5,+5) window. This information is useful for investors wanting to develop trading strategies around cross-listings.

6. Conclusion

6.1 Conclusion

This paper has aimed to verify the existence of CAARs around cross-listings before moving on to test any specific hypotheses. This was expected as cross-listings increase awareness and provide access to more investors for a particular cryptocurrency. The results show that CAARs are 6.7% in the (-3,+3) event window around the cross-listing, significant at the 5% level, as well as a decline in returns following the cross-listing. CAARs are significantly positive on t-2, t-1, and t=0 as well as significantly negative on t+2. These results contain important implications for investors and traders who want to know when to open or unload their cryptocurrency positions.

The first hypothesis aimed to test whether Bitcoin Dominance has a negative impact on CAARs. This has been tested through an OLS regression which confirmed the hypothesis at the 10% significance level. Using Bitcoin Dominance as a dummy variable led to a similar, yet statistically insignificant result. Trading Volume and Market Capitalization were added as control variables but were statistically insignificant. Exchange- and year dummies were added for robustness purposes. No literature on this topic had so far been established.

The second hypothesis examined the differences in CAARs observed in cryptocurrencies with different consensus mechanisms, namely PoW, PoS, and DPoS. Using a regression, in which Consensus mechanism was treated as a dummy variable, PoW- and DPoS- saw lower CAARs than PoS cryptocurrencies although only the PoW group was statistically significant for the (-3,+3) window. The one-way Anova and Tukey HSD test, added as a robustness check, confirmed the regression result although only for the (-1,+1) and (-5,+5) windows.. The Tukey HSD test showed that CAARs are significantly higher for the PoS- than for PoW group with a difference of 15% and 22% respectively for these windows. This is in line with hypothesis 2a. The difference between the (-1,+1) and (-5,+5) window is a result of the negative drift seen after the listing (see *Figure* 2) which appears to be non-existent for PoS cross-listings. This is valuable information for traders and holders alike to decide when to on- or offload their position. No literature on this topic had so far been established.

The sample is only fully representative for a population of cryptocurrencies that have been listed between 6 June 2018 and 19 March 2020 on one of the 14 centralized exchanges and have been tracked by coingecko.com. Although ungrounded in research, I believe that the results are applicable to larger time frame as well as other centralized exchanges. I also expect these results to not be materially different for other positive events related to cryptocurrencies, such as any crypto partnerships or cross-listings on decentralized exchanges.

6.2 Limitations and Future Research

The main limitation of this paper is the shortage of data. Manually collecting data due to a lack of centralized sets comes along with tradeoffs. Although the Telegram bot did not report cross-listings for a bigger timeframe, it would have been beneficial to add data for a larger timeframe. 2017 saw cryptocurrency prices and public interest hit new ATH's almost every month whereas the used timeframe in this paper did not. 2021 has been similar to 2017 and future research would do well to include data from these years.

The second hypothesis had to be tested with an extremely small sample size (22 vs. 49 vs. 28). This increases the probability of type I and II errors and makes the results, despite statistical significance, harder to determine. The same applies to some of the fourteen individual exchanges which made up a very small portion of the sample, making individual exchange comparison futile. Increasing the sample size could therefore provide more detailed and trustworthy outcomes. Exchange-specific Trading Volume would also enhance the result of this analysis, but extracting such data was beyond my resources.

Although this paper was specifically aimed at cross-listings which refers to every listing beyond a primary listing, having information on the frequency a specific cryptocurrency had already been listed could be beneficial to predict CAARs. I could not retrieve this data, but future research could aim to do so, and see whether a significant impact exists.

The length of the estimation window has been put at 21 days. Although other reasons for this length apply too, extending the estimation window until after the event window could have proven useful to obtain more accurate CAARs. This is often done in M&A papers such as Capron and Pistre (2002). Future research could follow this example although overlap of other cross-listings of the same cryptocurrencies must be considered.

Another limitation is the lack of comparable research. To my knowledge there have only been two other papers researching cryptocurrency cross-listings of which only one used a similar methodology. The research standards for stock listings have seen a lot more development and it is therefore that parts of the methodology (e.g., CAARs) have been obtained from these papers rather than cryptocurrency literature. Assumptions in traditional finance papers might not apply (as much) to cryptocurrencies and a new literary framework is required. Until then, it is important to realize that cryptocurrencies are still a recent phenomenon which are undergoing a volatile development before reaching maturation. Future researchers would therefore do well to keep track of- and incorporate these developments in their papers.

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Appendices

Appendix A: Dataset and Sample

Table 9: Dataset of all cross-listings.

All listings	2051
Non-daily listings	492
Daily listings	1559
Decentralized exchange listings	388
Price data unavailable at least 30 days before listing	297
Price data unavailable for listed tokens	197
Stablecoin listings	50
Listing of original tokens in derivative form	37
Similar tokens cross-listed during the estimation / event window	89
Cross-listings available for sample	500
Sample size based on Israel (1992)	222

Equation 1: Formula used to calculate the appropriate sample size based on Israel (1992).

$$n = \frac{N}{1+N(e)^2} = \frac{496}{1+496(0.05)^2} \approx 222$$

Table 10: Overview of all cross-listings per exchange.

Exchange	# of cross-listings in dataset	# of usable cross-listings in dataset	# of cross-listings in sample
Bibox	52	12	7
Binance	78	29	12
Bitfinex	87	24	11
Bithumb	98	57	28
Bittrex	151	82	40
Coinbase	22	17	10
Gate.io	77	16	7
Hadax*	16	5	3
HitBTC	182	91	39
Huobi	125	63	30
Idex (dec.)	388	NA**	NA**
KuCoin	138	56	20
OKEx	58	22	8
Poloniex	6	2	1
Upbit	80	20	6
Total	**1558**	**496**	**222**

*Hadax was incorporated by Huobi on 19 September 2018.

** Entries from Idex were not used, given that decentralized exchanges are outside the scope of this research (see *Literature Review*).

Appendix B: Summary statistics

Table 11: Summary statistics of all hypothesis related variables.

Variable	Description	N	Mean	Median	SD	Min	Max	Source
Market Capitalization	Logarithm of a cryptocurrency's average Market Capitalization over the estimation window in USD.	174	7.51	7.39	0.82	5.47	9.71	coingecko.com
Trading Volume	Logarithm of a cryptocurrency's average Trading Volume over the estimation window in USD.	214	6.17	6.23	0.07	3.79	9.48	coingecko.com
Bitcoin Dominance	Scale variable that represents the proportion of the cryptocurrency market made up by Bitcoin.	222	60.49	58.88	6.80	44.87	72.18	trading view.com
Bitcoin Dominance Dummy	Dummy variable that takes the value of 1 if Bitcoin Dominance is high, 0 otherwise.	222	0.41	0	-	0	1	trading view.com
Consensus Mechanism	Nominal variable that can take the value of PoW, PoS, or DPoS.	99	-	PoS	-	-	-	messari.io
Exchange	Dummy variable that accounts for the exchange on which the cryptocurrency was cross-listed.	222	-	HitBTC	-	-	-	Telegram Bot
Year	Dummy variable that accounts for the year in which the cross-listing took place.	222	-	2019	-	-	-	Telegram Bot

Appendix B: Summary statistics (continued)

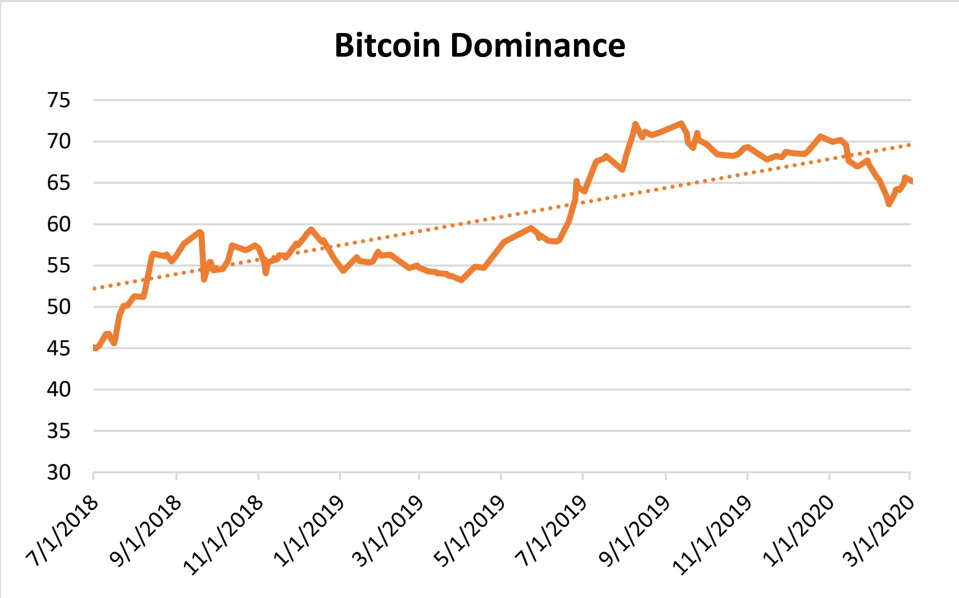

Figure 3: Bitcoin Dominance over the time frame of the sample set.

Appendix C: Results

Table 12. All event windows and corresponding t-test values as well as their confidence interval.

Event Window	t	df	Two-sided P	Mean	Lower*	Upper*
(-3,+3)	2.259	221	0.025	0.067	0.009	0.126
(-5,+5)	1.815	221	0.071	0.071	-0.006	0.147
(-3,-1)	2.670	221	0.008	0.046	0.0120	0.0797
(0,+3)	0.931	221	0.353	0.021	-0.024	0.067
-3	1.284	221	0.201	0.010	-0.005	0.025
-2	2.454	221	0.015	0.018	0.004	0.033
-1	1.738	221	0.084	0.018	-0.002	0.038
0	3.249	221	0.001	0.052	0.021	0.084
+1	-1.208	221	0.228	-0.010	-0.026	0.006
+2	-1.892	221	0.060	-0.018	-0.036	0.001
+3	-0.430	221	0.667	-0.003	-0.191	0.012

***** 95% confidence interval.

Table 13. CAARs listed for all fourteen exchanges for the (-3,+3) event window. The Market Model is used with Bitcoin functioning as a reference market.

Exchange	**CAAR (-3,3)**	**t-statistic**	**% positive**	**n**
HITBTC	-0.041	-1.041	0.42	41
BITTREX	0.207	2.291	0.67	39
HUOBI	0.069	0.846	0.57	30
BITHUMB	0.115	0.916	0.54	28
KUCOIN	0.019	0.269	0.67	18
BINANCE	0.081	0.464	0.33	12
BITFINEX	0.059	0.801	0.64	11
COINBASE	0.065	0.994	0.50	10
GATE.IO	0.170	0.972	0.50	8
UPBIT	0.042	0.423	0.43	7
OKEX	0.017	0.175	0.57	7
BIBOX	-0.105	-1.342	0.29	7
HADAX	-0.097	-1.878	0	3
POLONIEX	-0.118	NA	0	1

Table 14. Test of Homogeneity of Variances for all three Consensus mechanism groups across three event windows.

Levene's test	Levene statistic	*p*
(-3,+3)	2.344	0.101
(-1,+1)	1.493	0.257
(-5,+5)	1.052	0.353