ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Financial Economics

Ex-Post Performance of Initial Coin Offerings

ABSTRACT – This paper studies Initial Coin Offering (ICO) performance. It links short-term ICO performance to long-term ICO performance. The final data sample contains 241 ICOs in a timeframe reaching from April 2013 to October 2019. The results demonstrate that ICO underpricing is 124 percent, and market-corrected ICO underpricing is 126 percent. This confirms previous research done on ICO underpricing. Furthermore, the raw average buy-and-hold returns are positive, where average market-corrected buy-and-hold returns are negative. These findings are in line with traditional IPO literature, showing long-term underperformance and variables such as trading volume and issue size moderately justify this.

Name Student: Mike Ooijevaar

Student ID Number: 504520

Supervisor: Mr. Haikun Zhu

Second assessor: xxx

Date final version: 29 April 2020

ERASMUS UNIVERSITEIT ROTTERDAM

ERASMUS SCHOOL OF ECONOMICS

Table of contents

1. Introduction

Where crude oil was considered the highest valued resource, it now is data (the Economist, 2017). The use of data is increasing, and the possibilities are endless. After the financial crisis in 2008, the birth of Financial Technology (FinTech) was a fact. This crisis was a trust breach causing a global demand for technological developments improving trust and transparency (Menat, 2016). In line with this, Nakamoto (2008) constructed what is called blockchain: a peer-to-peer system to process electronic payments. Accordingly, he invented the first electronic coin: Bitcoin. Any other coin other than Bitcoin is considered an 'altcoin' (alternative to Bitcoin). Bitcoin is an exchange medium and can be called a cryptocurrency. An altcoin can be a cryptocurrency or a token. A cryptocurrency is an exchange medium. However, when a cryptocurrency is a token, it can also have other properties. Many of the founders of these so-called cryptocurrencies and tokens saw the opportunity to raise capital to fund their ideas.

The way to raise funding capital for these coins would be through an Initial Coin Offering (ICO). An ICO is the cryptocurrency version of the traditional Initial Public Offering (IPO). The main difference is that during an IPO stock is issued, while an ICO company sells cryptocurrencies, or tokens to raise capital (Felix & von Eije, 2019). Another difference is the maturity of the markets. The IPO market is the mature market, and the ICO market is relatively young. Moreover, IPO investors mostly hold onto their shares to sell them in the future at a higher price, which is the same for ICO investors holding tokens. However, the high volatility of the ICO market causes a higher level of short-term trading of tokens, and most of them do not offer any returns through dividends. IPO shares often offer dividends, and this increases the incentive to hold onto your shares in the long-term. Some research focuses on the short-term performance of tokens after an ICO (Adhami et al., 2018; de Jong et al., 2018; Felix & von Eije, 2019 and Momtaz, 2018), but very little on long-term performance (Momtaz, 2019). The focus of this research will be on bridging the gap between short-term and long-term ex-post ICO performance. Including multiple variables explaining ex-post performance and extending the time-frame of previous analyses enables the possibility to do more extensive research, making this study unique. This results in the formulation of the research question:

Is there successful ex-post Initial Coin Offering performance?

This paper adds scientific value to the field of ICO research. It has one of the largest initial ICO Coinmarketcap (CMC) dataset (2,321 ICOs) compared to other research done on this topic so far. With this research, I have the intention to explain the ICO process and the fundamental drivers of an ICO. I link ICO information and academic research. This adds to the understanding of the reader from the rise of FinTech up to long-term ex-post ICO performance. Furthermore, I look at both short-term and long-term performance, including the cryptocurrency crash at the beginning of 2018 showing impressive results.

This paper contributes to ICO research as it bridges the gap between short-term and long-term performance, looking at underpricing and buy-and-hold returns. It confirms previous research and demonstrates that underpricing exists in ICOs. Average underpricing is 126 percent, and market-corrected underpricing is 124 percent. Furthermore, it shows that there is positive short-term ICO performance reflected by positive average raw and market-corrected buy-and-hold returns. Additionally, long-term ICO performance shows average positive raw buy-and-hold returns and average negative market-corrected buy-and-hold returns. Besides, this research includes two analyses, showing the impact of trading volume, issue size, and other independent variables on underpricing and buy-and-hold returns. Trading volume has a significant positive effect on underpricing, but not on buy-and-hold returns. The issue size shows significant results with negative coefficients instead of expected positive coefficients. Furthermore, it shows that other variables also impact long-term performance. For instance, if there was a retained percentage of the offering, whether the market is hot or if a token had a pre-ICO before the actual ICO. The results confirm what previous research has shown on ICO underpricing and open for further research on long-term buy-and-hold returns.

This research offers investors, who are either well-informed or not, a look at how FinTech, blockchain, and the ICO market developed over the years. Moreover, this paper demonstrates that the performance of a token does not solely rely on speculation, luck, or a solid investment idea. Multiple factors must be considered given that everyone could transform an idea into an ICO to obtain funding. It also shows that multiple factors impact ICO performance, given that everyone could transform an idea into an ICO to obtain funding. Besides, this paper shows that rules and regulations are essential to govern the ICO market and prevent issuers and investors from fraud, speculation, and money laundering. A solid KYC (Know Your Customer) process for both the issuer and the investor can be a solution for this.

The paper has the following structure. Section 2 discusses earlier studies done on the topics blockchain, cryptocurrencies, ICOs, IPOs, ICO underpricing, and ex-post ICO performance.

Section 3 explains and substantiates the hypotheses which this paper tests. Section 4 defines the methodology. The next section (5) includes the collection and the use of the data, as well as the descriptive statistics. Section 6 discusses the results of this research. Finally, Section 7 gives a conclusion, followed by future recommendations and insights on further research.

2. Literature Review

This section provides the theoretical background of this study. First, I introduce FinTech with the intention to increase the understanding of the developments within FinTech into blockchain technology. Second, I will discuss what an ICO is and what the differences are to the more traditional IPO. The third section explains ex-post performance by discussing both underpricing and market cycles, making the distinction between short-term and long-term.

2.1 FinTech, Blockchain and Cryptocurrencies

After the collapse of the banking system in 2008, people required financial innovation, which was accompanied by extensive use of data. This crisis caused a lack of trust in the current system and the emergence of FinTech and its corresponding growth. FinTech companies were able to offer this by increasing trust, transparency, and technology (Menat, 2016).[1] Nowadays, nearly everyone who has telephones and tablets to do online payments, use applications to check their balance on their bank account, or does a contactless payment in a shop is contributing to this billion-dollar industry. The financial sector is changing rapidly due to these developments. It creates both opportunities as well as challenges for governments, institutions, and consumers. Forbes (2018) even spoke of a FinTech revolution impacting the financial industry.

FinTech companies have changed the rules of the game of the financial sector tremendously. Today people can pay with their mobile phones, request credit online quickly, and invest online with one click. Take Kenya, for instance, which pioneered a mobile banking system called Mpesa, which is owned by Vodafone. Kenyans can access their Mpesa accounts directly on their mobile phones to transfer money, pay bills, or take out loans. Today an estimated 96 percent of the households in Kenya use Mpesa. Suri and Jack (2016) found it has raised approximately two percent of Kenyan households out of severe poverty. The mobile banking system offered by Mpesa is a relatively simple tool that improved financial

[1] FinTech is a broad concept, which is not the focus of this paper. This is the reason that it is only briefly discussed in the introduction and builds up to the main subject of the paper: Initial Coin Offerings. For further reading on this topic, I would recommend assessing The Fintech Book written by Chishti and Barberis (2016).

transactions in Kenya. This shows how FinTech can change a country its whole banking system. This example is one of the many that show the impact of FinTech. However, it shows that this improved trust and offered transparency demanded by Kenyans.

Currently, blockchain technology and its cryptocurrencies influence the financial services industry. Blockchain technology is a public- and decentralized database, which consists of all the transactions using blockchain technology. It is one of the many revolutionary developments in FinTech.[2] Blockchain has a distributed ledger technology, which is neither controlled nor owned by a government, institution, or company. Moreover, it is the next step in FinTech development as blockchain offers the demanded transparency, regains trust, and is unchanging over time. However, it does need rules or regulations to secure safety for both the company and the investors as uncontrolled transactions can be prone to fraud.

A new transaction is always strung like a chain and attached to the existing data blocks, a blockchain. The system is continually being updated and traces all improper transactions immediately. These transactions are completed by using so-called cryptocurrencies. In other words, a cryptocurrency is a digital currency. These can either be currencies or tokens. When a cryptocurrency is just a currency it is just an exchange medium. However, when a cryptocurrency is a token, it can also have other properties such as dividends, accessibility of products or services, the right to vote, and the right of contribution. Investors can buy into these tokens before the launch of the token. This is possible when a company, which is offering a token, does an ICO.

2.2 Initial Coin Offerings

When a company would like to launch a new coin, an application, or a service, it can do so through an Initial Coin Offering. A company uses an ICO mainly as a fundraiser for the project (Hartmann et al., 2018). Other reasons for companies to engage themselves in these innovations are reducing costs and maintaining independence. The latter includes the avoidance of intermediaries and payment agents (Adhami et al., 2018). An ICO is done by going public and allowing investors to buy into the offering. As stated by de Jong et al. (2018), an ICO starts with the pre-announcement of the actual ICO. In this stage, the company sells the tokens privately until the sale is open to the public. Commonly, after the completion of the ICO, it is

[2] Currently, there are multiple fields of research that are changing the financial industry, such as blockchain, robotic process automation (RPA), artificial intelligence (AI), regulatory technology (RegTech), and conversational banking. I know that it could be that there are more developments at this moment or that I did not include all of the current developments at the time of writing this paper.

possible to trade the tokens for two weeks after the end of the funding campaign (de Jong et al., 2018). After this, it is possible to trade the tokens on secondary markets. Another important reason for engaging in an ICO is the market liquidity after the ICO (Momtaz, 2018). For most tokens that get listed on an exchange platform, it is possible to trade online 24 hours a day. Furthermore, the demand for low-threshold investments was growing. The process of a more traditional way of funding, Venture Capital (VC), is complicated to create and finalize due to government protection. Governments want to protect investors from investing in projects that eventually turn out to be worthless, causing the investors to lose their total investment. Companies must comply with these rules and obligations, making it a more complicated process. An alternative is investing in Kickstarter[3], but here the creators remain total ownership of the project. Investing in ICOs bridged the gap between VC and Kickstarter and allowed the investor to invest in an idea at an early stage and obtain ownership of the tokens bought.[4]

The ICO market is relatively young compared to the traditional IPO market, but it already has substantial overall value. The total value of funds raised by the end of 2018 was nearly 24 billion dollars (ICObench, 2018).[5] According to Elementus (2018), it reached even over 28 billion dollars by August 2018. In 2018 we saw an increase to 11.5 billion dollars compared to approximately 10 billion dollars in 2017. The largest ICO was the EOS ICO, which raised 4.2 billion dollars between 2017 and 2018 (Appendix A, Figure A1). This ICO had a length of approximately one year. We can conclude that there was an increasing trend in ICOs, and funds raised in the last three years. However, the market performance in 2019 so far has been only a fraction of 2018, with a total amount of funds raised around 400 million dollars between January and August.[6]

2.2.1 ICOs vs. IPOs

A lot of research has been done on IPOs but not on ICOs. Highly valuable information can be obtained from IPO researches and adjusted and applied to ICO research. The reasoning behind this is that the IPO process is considered the precursor of the ICO process. Although the IPO process is different from the ICO process, it has similarities and includes useful

[3] Kickstarter allows to invest in projects where the creators remain full ownership of the work, and the intention of investing is not to make a return on your investment.

[4] These insights considering the position of ICO investments compared to VC and Kickstarter were obtained after an interview with PwC Blockchain Specialist Alex de Vries done on the 21st of November 2019.

[5] The ICO market analysis of 2018 gives insights on both ICO data and trends in 2018. Moreover, a comparison is made between 2017 and 2018 to see how to market has developed. For example, in 2018, the amount of ICOs ended was 3.5 times more than in 2017.

[6] ICOdata.io shows the amount of the funds raised per year, and in 2019 it had decreased considerably compared to previous years. Other articles use similar values.

information for ICO research. The amount of research on ICOs is growing, especially research on the process itself and short-term ICO performance. However, the amount of research on actual long-term ex-post ICO performance remains small. Only Momtaz (2019) gives some insights on long-term performance. De Jong et al. (2018), for example, analyze the factors of success for 630 ICOs, performed within the time frame of August 2015 and December 2017. They focus mainly on the phase between ICO pre-announcement and the actual trading day. Felix and von Eije (2019), on the other hand, focus on bridging the gap between IPOs and ICOs, ICO underpricing, and the actual trading date. They use CMC data as one of their central data sources. As this source contains daily pricing from the start of the ICO until the present, it is also a reliable source for long-term performance measurement.

Momtaz (2019) also uses CMC and mentions a significant limitation of this database. This limitation is that his database does not include data on actual determinants of long-term performance, and he does not include the initial offer price to measure underpricing. In this research, I will use the underpricing methodology and buy-and-hold methodology to measure both short-term and long-term performance. The actual testing of the sample tries to fill in in the limitations mentioned in Momtaz (2019) his research, where CMC is the only database used, and he does not include other explanatory variables to test long-term performance. During the process of constructing my database, I included explanatory variables and the initial offer prices. Unfortunately, this caused the overall sample to shrink. Moreover, Adhami et al. (2018) are the first to describe ICO specific characteristics and reveal the success factors of a fundraising process. Including specific ICO characteristics and success factors will contribute to this research investigating ICO ex-post performance. Accordingly, the following sections will first focus on the differences between ICOs and IPOs.

2.2.1.1 Regulation

Felix and von Eije (2019) were the first to extensively investigate underpricing in ICOs and accordingly explain the similarities as well as the differences in IPOs and ICOs. First, the regulations for IPOs vary compared to ICOs. Felix and von Eije (2019) state that ICO regulations were ‘weak and inconsistent’ in 2018. The ICO process is relatively new, and in the beginning, the rules and regulations were not yet there. If you had an idea, you could write it down in a whitepaper and obtain funding without any clear regulations.[7] Currently, the

[7] Adhami et al. (2018) thoroughly explain what a white paper is and its effect on the probability of a project’s success. A whitepaper describes the idea and the business plan when launching the token.

foremost concern of ICO investors is complex regulations resulting in higher costs or even failure to start an ICO. The following countries ban ICOs: South Korea, China, Nepal, Bangladesh, Macedonia, and Bolivia. Others, such as Ecuador, and Pakistan have banned altcoins. According to Momtaz (2018), the transaction costs of the ICO process are almost costless compared to IPOs and venture capital. The reason for this was that regulations of ICOs were similar to a crowdfunding process. Currently, the popularity is decreasing due to increasing regulations and costs, causing a decrease in the amount of ICOs.[8] The Dutch Authority for the Financial Markets (AFM), which is comparable to the US Securities and Emissions Committee (SEC), strongly advises on its website to avoid investing in ICOs. To do an IPO, companies have to inform these instances and comply with stringent regulations. For ICOs, these regulations are not there yet as they are complex to construct.

ICOs are a fast way of raising capital but often associated with fraud, speculation, money laundering, or having a misleading account of nature due to anonymity and unobservable ICO structuring. The SEC uses the so-called Howey Test (Momtaz, 2018) to make sure that the ICO token aligns with the securities regulation. Due to increased bans and regulations in the last two years, the amount of ICOs has decreased. However, the anonymity does remain within an ICO, and in case anonymity is preferred, there is no need to know your customer. The KYC process is an enormous obstacle within the ICO process as ICOs have obtained a negative reputation. In an IPO process, this is important as these mature companies want to keep a positive reputation. Transparency of investors and in internal company communication during and after an ICO will increase the trustfulness of ICOs.

Setting up a KYC process in which investors must identify themselves combined with a maximum number of tokens the investor can buy would be of great value. Combining ICO funding with VC funding will attract professional investors and increase the diversification of funding. This is in line with findings from Johnson and Yi (2019), which show that companies who are willing to adapt to specific regulatory mechanisms could make ICOs a reliable way of funding. Furthermore, this can lead to lower underpricing, improved performance, and increased ICO success.

[8] ICOdata.io, ICObench.com, and Coinmarketcap.com show that the ICO market has shrunk compared to previous years.

2.2.1.2 Young Companies versus Mature Companies

Well-established companies with strong growth potential, are in general, the companies that partake in IPOs. The companies that do an ICO are riskier and relatively young. The former, has a regulatory framework around it that safeguards investors from investing in new ideas, which could be unsuccessful. Therefore, only mature or developed companies can and will do an IPO. An IPO can function as a way for mature companies to extract capital or to cash out when the company is willing to sell. An ICO process starts after the completion of writing the whitepaper, extracting capital to fund the idea. Consequently, these differences cause varying process lengths for IPOs and ICOs.

2.2.1.3 Process length

Beforehand, the IPO process was lengthier than the ICO process due to more oppressive regulations. However, due to increased regulations for ICOs, the process became more difficult or even impossible for companies willing to do an ICO. The ICO companies must comply with these regulations, and it is not possible anymore to directly extract funding after writing down an idea. This increases the duration of an ICO and decreases the amount of ICO projects. The year 2019 shows a decrease in its funding raised by ICOs, which is considerably lower compared to 2017 and 2018. Although it seems that there are quite some differences in ICOs and IPOs, the actual listing day is the same. This is the first day a cryptocurrency trades on an exchange and the first day stock trades on an exchange. When a cryptocurrency lists on one exchange, you see it scatter over other exchanges on a fast pass. Whereas for stock exchanges it takes a considerably longer time to be adopted on another exchange (Felix & von Eije, 2019).

2.2.1.4 **Liquidity**

The ICO process is a fast way of obtaining capital and, as previously mentioned, varies compared to the IPO process when looking at after-market liquidity. Firms tend to underprice their tokens to create liquidity in the market (Momtaz, 2018). He also describes the advantage ICOs offer considering the voting rights of some tokens, which a person can simply transfer to another person. Previously, it was only possible to buy into an ICO process where the company itself was responsible for the fundraising. Furthermore, another difference in digital currency exchanges (DCE) compared to stock exchanges is that tokens trade for 24 hours every day of the week. Whereas stock exchanges are only open during weekdays from approximately 9:00 a.m. up to 6 p.m. Besides, the ICO process is changing to optimize, fasten, and improve security within the process. Howell et al. (2018) see liquidity as the central measurement for ICO success and find that liquidity and trading volume increases when the token discloses information, has project commitment and show quality. In this research, variables such as quality rating, funding target reached, retained percentage, and whether there was a pre-ICO sale before the actual ICO influence the project's liquidity.

In January 2019 a new offering process was introduced: Initial Exchange Offering (IEO). Tron's BitTorrent was the first to do an IEO, giving users the possibility to acquire tokens with funds straight from their exchange wallet.[9] This allows investors to have one wallet on your exchange account instead of different wallets on different blockchains. This new offering can be seen as a potential turning point in the cryptocurrency market, bringing back the trust the investor initially needs to continue in the fundraising process. This could be an alternative to the traditional ICO process, improving ex-post ICO performance. The next section will give a broader explanation of short-term and long-term performance.

2.3 Short-term and long-term performance

Short-term is considered the period of the 1st day of trading to one month after the 1st day of trading. A full market-cycle can take three up to five years. It is seen as a regularity in IPO research to verify underpricing with initial abnormal returns. To verify this, I use the 1st day of trading to the 5th, 10th, and 20th trading (Chi & Padgett, 2005). This is equivalent to using one day, one working week, two working weeks, and four working weeks. In the ICO market, trading is possible, 24 hours per week, following this, I use one day, one week, and one month. I leave out the two working weeks as I also investigate long-term performance up to three years after the ICO.

The cryptocurrency market is a relatively young and highly volatile market, which allows obtaining extremely high profits as well as great losses both in the short-term and long-term. First, performance will be measured by looking at differences between the initial offer price and daily pricing. Secondly, section 6 shows how the regression analyses test long-term performance.

2.3.1 Market Cycles

Market cycles vary from short-term to long-term, but all show the same stages of cyclicality. The price fluctuations of the principal indicator of the market, Bitcoin, also show a

[9] https://www.binance.vision/glossary/initial-exchange-offering explains the concept IEO. Binance is the largest exchange for cryptocurrencies by traded volume and the first to set-up an IEO platform.

pattern. If we specifically look at Bitcoin's cycles, there are four clear periods of severe bull markets (uptrend) and bear markets (downtrend). Moreover, there was a cryptocurrency crash in January 2018. Etoro.com[10] (Appendix A, Figure A2-4) shows that there are five periods, which can be labeled as up, down, lower lows, support, and breakout. This whole cycle occurred from 2011 to 2012 and 2014 to 2016. Currently, the market shows similar developments, and this defines another support phase. However, due to the high volatility in the market, it is hard to estimate whether tokens are correctly priced, overpriced, or underpriced. The price development of Bitcoin, for instance, varies from approximately $3,500 per token up to $13,000 per token. Market cyclicality is used to make price estimations but remains a difficult task in the highly volatile cryptocurrency market. The value of the market reflects the fluctuations of the leading indicators in the market, such as Bitcoin and Ethereum. Yet a large part of the price-setting in the market remains speculative. The price setting, in this case, is highly influenced by information asymmetry (see section 2.3.2). Measuring underpricing and estimating long-term performance is interesting when analyzing market developments over the years.

2.3.2 Underpricing and Long-Term Ex-Post Performance

Underpricing occurs when the closing price of a stock is higher than the set initial public offer price after the first day of trading. This short-run phenomenon occurs in many IPO markets (Chan et al., 2001), and IPO literature broadly documents underpricing. Ritter (1991) makes the distinction between three anomalies in the pricing of IPOs: (1) underpricing, (2) "hot issue" market, and (3) long-run IPOs are overpriced. This research, combined with ICO research (Adhami et al., 2018; Lee et al., 2018; Momtaz, 2018 & 2019; Felix & van Eije, 2019), can be used to bridge the gap between IPOs, ICOs, underpricing, and long-term performance.

The theorem, which is the foundation of explaining information asymmetry, is the 'lemons problem' (Akerlof, 1970). This theorem can explain underpricing in IPOs. In IPOs, this can be the case as the issuer of the shares has information on the company, which the investor lacks. Although this process is highly regulated, the company must provide company information and comply with all regulations before it can do an IPO. Furthermore, there is a managing underwriter acting as an intermediary with the motivation to price correctly. The information mismatch in ICOs can be even greater as anyone could create a white paper and take on funding

[10] Etoro.com is a social trading network created in January 2007. In 2017 they added cryptocurrency trading to their offering. In 2019 they made an overview of Bitcoin its price development over the years (Appendix A, Figure A1).

by doing an ICO. Furthermore, there is no intermediary, and most countries lack the regulations a company must comply with before an ICO. This causes small and large ICO investors to face a high level of uncertainty.

The high levels of information asymmetry and uncertainty cause the fact that ICO investments can be highly successful as well as extremely value-destroying. Furthermore, the highly volatile market consists of properly informed investors who cause a certain increase in investments when the market is bullish. This will trigger other (uninformed) investors to have a fear of missing out during this market upstate. However, when the market continues to develop and becomes bearish, these upstate investors may lose a lot of money. This refers to the so-called winner's curse model in which there are a group of well-informed investors and a group of uninformed investors, which is the most important underpricing model (Rock, 1986). A company only does an ICO once, so the company has the incentive to maximize the funding obtained through an offering. However, due to the lemons problem and the information mismatch, the coin is underpriced after the offering. The money that the company does not earn by this underpricing effect is called "money left on the table" (Loughran & Ritter, 2012; Felix & van Eije, 2019). Higher levels of transparency through the inclusion of quality ratings, bonus schemes, and pre-ICO fundraising from these offering companies could decrease the lemons problem and improve the performance of an ICO.

Underpricing of ICOs is not that broadly documented as the underpricing of IPOs. Moreover, only a few interpret traditional IPO literature and connect it to ICO research. Momtaz (2018) finds that the average underpricing per firm is 8.2 percent. This results in an amount of $1.1 million, which is lost. He finds average underpricing for 15 percent of all ICOs. Moreover, on the first trading day approximately 40 percent of the offerings lose value (Momtaz, 2019). Felix and von Eije (2019) also obtain results showing underpricing. Their research shows average ICO underpricing of 102 percent. They broadly compare IPO and ICO literature, which consider underpricing and conclude that these levels are considerably higher than the levels of IPO underpricing. During the fundraising process, it becomes clear whether the token its initial offer price was priced correctly, overpriced or underpriced. According to Benedetti and Kostovetsky (2018), underpricing exists, and the token's returns are almost 180 percent after a holding of 16 days. Previous research focuses on the period of ICO pre-announcement up to the actual ICO and the first trading day after the ICO, but the results are varying. Combining this with the fact that little research concentrates on long-term performance ICO performance shows that this research contributes to academic ICO research.

Long-term performance in traditional IPO researched is usually measured by calculating raw buy-and-hold returns and correcting this with a market benchmark (Ritter, 1991). Many IPO studies find that stocks underperform in the long-run. Ritter (1991) states that this underperformance depends on three things; risk mismeasurement, bad luck or fads, and overoptimism. By using a benchmark, when measuring buy-and-hold returns, risk mismeasurement is not possible. Bad luck fades when using cross-sectional data. Moreover, new companies in the early stages of development show underperformance, such as companies in the ICO market. This does not exclude bad luck as a benchmark for underperformance, but it does reflect an overoptimistic state of the ICO market, where investors follow fads. Moreover, Ibbotson et al. (1988) found that an increasing amount of new issues, a market is considered to be hot, reduce initial returns by six to twelve months.

Ritter (1991) addresses the fact that investors can be overoptimistic in valuing their earning potential, which is in line with the winner's curse model. Companies are aware of this and play into this optimism. Companies starting an ICO project are more prone to do this and create a situation in which the investor is exposed to the lemons problem and is not able to avoid it. Overoptimistic investors buy into the offering and do not value the tokens properly. An ICO has no intermediary, so its success depends on the information the investor holds. Lee et al. (2018) refer to this as the wisdom of the crowds. In the ICO market, investors more often follow the behavior of other investors instead of relying on their own investment choices. Schiller (1990) refers to this as fads, showing whether the market is "hot" or not. The information asymmetry bias can be solved when the investor holds enough information. Lee et al. (2018) give two solutions for this: company certification before the offering and controlling the wisdom of the crowds.

According to Purnanandam and Swaminathan (2004), long-term IPO underperformance can be predicted by initial overpricing. Moreover, they find that IPOs with higher first-day returns underperform in the long run. Furthermore, Miller (1977) says the most optimistic investors buy into the offering. When valuing a firm, investors have similar expectations, but over time the valuations will move towards each other that causes the price to drop. From an ICO perspective, investors base their decisions on the availability of information. When the issue size grows, it will increase the amount of research on this specific ICO, and more information becomes available. If this occurs, larger ICOs will be overpriced more frequently than smaller ICOs. This is in line with the findings of Momtaz (2019), who state that the larger ICOs show long-term underperformance.

Loughran and Ritter (1995) found that in the United States there was significant stock underperformance in three to five years after the offering. Therefore, Chan et al. (2001) measure long-term performance for Chinese IPOs three years after the listing. In the research of Ritter (1991), he also uses the previously called 'after-market period' consisting of three years. From an ICO perspective, Momtaz (2019) also uses a time-frame of one week up to three-year buy-and-hold returns. Combining previous research and the final regression analyses sample cause that the maximum amount of years in this research will also be three.

Moreover, long-term performance can only be measured and tested by analyzing multiple factors. Whether a token is still tradable or if the token lists on CMC, ICObench or another principal ICO information provider.[11] Additionally, was the website active after the ICO[12], or did the ICO include a bonus scheme. More variables are important in this research. Section 3 defines these variables after the description of the hypotheses.

3. Hypotheses

This section provides the hypotheses tested within this research. First, it will give the reasoning for the distinction between short-term and long-term performance. Second, an explanation of information asymmetry and its importance in ICO performance research. Lastly, I extensively explain the variables used in this research, starting with the two main variables and finishing with a variable overview, which includes all variables.

3.1 Short-term and long-term ex-post performance dependent variables

The performance of a token after an ICO is highly volatile. Investors can obtain high returns both in the short-term and long-term. When the market is bullish, investors can obtain high returns, but many investors also lose their total investments. Traditional IPO literature provides us with the information that underpricing exists and that IPOs show long-term underperformance. This information can be linked and modified to ICO research.

From a short-term perspective, Loughran and Ritter (2002) find that an average IPO leaves $9.1 million on the table, meaning that the share could have been sold for a higher price as the market would have been willing to pay more. The closing price on the first day, in this case, is higher than the initial offer price causing companies to leave money on the table. From an ICO

[11] When a token lists on sources like CMC, ICObench, ICOdrops or another main ICO information provider a token is still performing. When there is no data available, and the token's website is offline, it confirms that the token has perished and is not performing anymore.

[12] I did a manual check on the testing sample. If a website is active, the corresponding token is considered alive and active. When the website does not exist, the token has perished and is not active. If so, I erased the token from the sample.

perspective, Adhami et al. (2018) state that the process of an ICO consist of high levels of information asymmetry and uncertainty when compared to other existing businesses. Moreover, Felix and von Eije (2019) also broadly examine information asymmetry and its effects on ICO underpricing. They found that there was average ICO underpricing of 102 percent with a median of 26 percent. Thus, the ICO market shows even higher levels of underpricing compared to the traditional IPO market. Additionally, Momtaz (2018 & 2019) found that 40 percent of the offerings lose value on the first trading day. Consequently, this means that in the ICO market, there is also money left on the table.

Momtaz (2019) investigates long-term buy-and-hold returns and found that these were positive for the mean. As previously stated, the literature shows that investors can be prone to the winner's curse model and companies playing into this over-optimism. ICO companies are more inclined to do this, and investors have a higher chance of facing the lemons problem. When combining both the literature and the results, I do expect that raw buy-and-hold returns will be positive on average due to the large amount of ICOs done in this relatively young and highly volatile market. Moreover, given the IPO literature, it is common that IPOs underperform in the long-run. Besides, from an IPO perspective (Ritter, 1991; Ritter & Welch, 2002) found that market-corrected buy-and-hold returns were negative over three years in every subperiod. When correcting buy-and-hold returns for the market, it provides us with a more reliable outcome compared to the raw buy-and-hold returns Even more for the ICO market, as the market is highly reliant on the pricing of the more substantial tokens, such as Bitcoin and Ethereum (Nadler & Guo, 2020). Therefore, this research also calculates market-corrected returns.

Taking previous IPO and ICO literature into account, I expect, that in the short-term there will be underpricing and positive first-day returns. Moreover, in the long-term, I expect positive average raw buy-and-hold returns, but negative long-term performance when taking average market-corrected buy-and-hold returns. This leads to the following hypotheses.

H1 ***Short-term performance***

a. There was average ICO underpricing.

b. There were positive average ICO raw first-day returns.

c. There were positive average ICO market-corrected first-day returns.

H2 ***Long-term performance***

a. There were positive average ICO raw buy-and-hold returns.

b. There were negative ICO market-corrected buy-and-hold returns

IPO literature gives evidence that there is underpricing and long-term underperformance. The younger and more volatile ICO market results show that value drops in the short-term, but in the long-term, there could be positive average raw buy-and-hold returns. The next section describes the explanatory variables and the last two hypotheses.

3.2 Short-term and long-term explanatory variables

This section documents the two main explanatory variables: trading volume and issue size. For the short-run, research broadly documents the IPO underpricing phenomenon (Ritter, 1991; Chan et al., 2001; Loughran & Ritter, 2002; Ritter & Welch, 2002; Gandolfi et al., 2018), and this is also the case for ICO underpricing (Adhami et al., 2018; de Jong et al., 2018; Momtaz, 2018; Felix & von Eije, 2019). In the long-run, IPOs often underperform (Ritter, 1991), and Momtaz (2019) obtains similar results for ICOs. When ICOs grow larger, they are more frequently overpriced and show long-term underperformance (Momtaz, 2019). From an ICO perspective, it would be interesting to bridge the gap between short-term and long-term ICO performance. Ritter (1991), found that on average, the smaller offerings show the highest initial returns and have the worst after-market performance. In the short-term trading volume shows the demand and interest of investors in the short-term. In the long-term, it tells whether the investor follows a buy-and-hold strategy, or the market shows high trading intensity. I expect that trading volume has a positive effect on short-term performance, but a negative relationship with long-term performance. The issue size, on the other hand, incorporates an increasing amount of information when the size increases. I assume information asymmetry between the company and the investor to decrease and cause a positive influence on ICO performance both in the short-term and the long-term. Taking this into account, trading volume and issue size incorporate the most information considering short-term and long-term ICO performance compared to the other variables used in this research. The next two sections will give further substantiation for the use of these two variables and their expected signs of influence both in the short-term and long-term.

3.2.1 Trading volume

The first day of trading, or the so-called listing day, of an ICO, shows how high the interest of investors is in that specific offering. The company sets the offer price, and when trading starts, the price will move to the market value. The level of trading volume on the first day of trading also shows whether the investors are interested in investing in this ICO. The amount shows how often the number of tokens changed hands on a listing day. The amount of ICOs was increasing up to 2017, and this caused a considerable increase in trading volume (Momtaz, 2019). In IPO research, the samples are often being grouped depending on whether the IPO has a positive or negative level of underpricing (Miller & Reilly, 1987; Schultz & Zaman, 1994). The groups with positive underpricing levels show a more substantial amount of trading volume on the first trading day. This research reflects this in a sample of 263 ICOs. The negative group's (88) trading volume is 2 percent of the positive group's (175) trading volume (Appendix B, Table B1). For the long-term, Ritter (1991) finds that in years with high-volume offerings, the performance was worse compared to low-volume years. Combining this with the previously stated findings of Momtaz (2019), that ICOs are more frequently overpriced and show long-term underperformance make me expect that trading volume has a positive influence on performance in the short-term, but a negative influence on the long-term. Besides, the median, minimum, and maximum are lower for the negative underpricing (overpricing) group compared to the (positive) underpricing group (Appendix B, Table B1). Furthermore, Beatty and Ritter (1986) find that the underpricing level is directly linked to the ex-ante uncertainty of an offering its value. The reason they find for this is that ex-ante uncertainty and the winner's curse are positively correlated. This leads to the following hypothesis.

H3 *Trading volume has a positive relationship with short-term performance*

3.2.2 Issue size

The issue size, the offer price multiplied by the natural logarithm of the number of tokens, contains a lot of information before the offering. The lemon's problem theorem explains underpricing in the short-term, but I also expect it to influence long-term ICO performance. We must keep in mind that the ICO market is a highly speculative market consisting of a large amount of information asymmetry. The company doing a project can vary from an operating company to a single person writing an idea on a whitepaper. Thus, the issuer in the ICO market is the first to provide information to potential investors. In the IPO market, the issuer often is a well-established company, which has a lot of accessible (public) company information. These well-established companies show larger issue sizes and have more information available (Miller & Reilly, 1987). In the IPO market, it is even an empirical regularity that, on average, a smaller offering is more speculative than a more substantial offering (Ritter, 1985; Beatty & Ritter, 1986). From an ICO perspective, I expect the more substantial issues to contain more information, which is in line with the IPO regularity. This will mean that ICOs with a larger issue size cause an investor to have more information before investing in an ICO compared to an ICO with a smaller issue size. When an ICO issue becomes more extensive, it gives more incentive for both the issuer as well as (academic) researchers to provide information. Moreover, the demand for more information enlarges from an investor's perspective as a larger issue decreases information asymmetry and increases expectations. I expect the short-term and long-term ICO performance to reflect this positively. This leads to the following hypothesis.

H4 *There is a positive relationship between issue size and long-term performance*

This section only describes and discusses the dependent variables and the two main explanatory variables. The next section 3.3, states and discusses all other variables. Furthermore, there is an overview of all different variables and their descriptions.

3.3 Variable Overview

This section shows the variables this ICO performance research uses. The next section describes the dependent variables, and Section 3.3.2 lists the main explanatory variables. The first variable, trading volume, is expected to have a significant influence in the short-term and the second, issue size, in the long-term. The variables that follow are all control variables, with the last four variables being dummy variables. The table gives variable explanations and the expected coefficient signs both in the short-term and the long-term.

3.3.1 Dependent variables

This research uses multiple dependent variables to measure ex-post ICO performance. First, underpricing is measured, which divides the listing day closing price minus the initial offer price by the initial offer price. The next independent variable is market-corrected underpricing. Furthermore, buy-and-hold returns are independent variables. Buy-and-hold returns are calculated by taking the closing price of that particular trading day, subtracting this by the opening price of this specific day, and dividing this by that opening price. These returns are organized in the following order, BH1 up to BH8 and MBH1 up to MBH8. These are the returns for the first day of trading, in one week, in one month, in three months, in six months, after one year, after two years and after three years.

3.3.2 Independent variables

Table 1 below gives an overview of all independent variables, which all the regressions conducted within this research include.

Table 1: Explanatory Variable Description

This table summarizes the different variables used in the regression analysis. The 1st column on the left provides the variable name. The 2nd column explains what the variable is and its corresponding measurement.

Explanatory variables	***Description***
Trading volume	*The natural logarithm of the trading volume in US$ at the day of listing*
Issue size	*The offer price multiplied by the natural logarithm of the number of tokens offered*
Control variables	
Offer Price	*The initial offer price in US$ at which the tokens are offered during an ICO*
Quality rating	*On ICObench each token is rated with the rating value varying between 1 and 5, with 5 being the best possible rating*
Market sentiment	*The cryptocurrencies index (CCI30) can be used as an industry benchmark for market sentiment*
Funding target reached	*The percentage of the funding target that is reached, which is the offer price times the number of tokens offered*
Retained percentage	*The retained percentage of tokens which is not offered during the ICO in US$.*
Category	*The category in which the offering was completed (33 categories)*
Country	*The country in which the offering was completed (46 countries)*
Platform	*The platform on which the offering was completed (18 platforms)*
Dummy variables	
Hot issue market	*A dummy variable which has the value of 1 if the market was in a 'hot' period and 0 otherwise*
Pre-ICO	*A dummy variable which has the value of 1 if tokens were available for sale before the official ICO and 0 otherwise.*
Currency	*A dummy variable which has the value of 1 if the token is a currency and 0 otherwise*
Bonus scheme	*A dummy variable which has the value of 1 if early investors can get a discount during the ICO period and 0 otherwise*

The next section explains the methodology of this research and shows the formulas of the dependent variables both as short-term and long-term measurements. Furthermore, the regression analysis is explained and visualized in an equation.

4. Methodology

This section will describe and explain the methodology used in this research. First, looking at the methodology to measure short-term performance by looking at the initial offer price of a token before an ICO and comparing this to pricing on the first day of trading. Second, the methodology to measure long-term performance by looking at buy-and-hold returns at a specific holding period (one day, one week, one month, three months, six months, one year, two years, and three years). Third, the regression analysis gives an overview and provides an explanation for this research its explanatory variables of ex-post performance.

4.1 Short-term performance measurement

This research uses a standard model for underpricing and first-day raw returns. In general, IPO and ICO research use these methods. Each measurement has a description and a formula.

Underpricing

Formula 1 shows the equation for ICO underpricing, UP_i. The equation divides the listing day closing price, P_i, minus the initial offer price, O_i, by the initial offer price, O_i, of the specific selected ICO.

$$UP_i = \frac{P_i - O_i}{O_i} \tag{1}$$

Market-corrected underpricing

Formula 2 shows the equation for ICO market-corrected underpricing, MUP_i. Correcting underpricing (and raw returns) for the market is common in both IPO (Ritter, 1991; Chan et al., 2001) and ICO research (Felix & von Eije, 2018; Momtaz, 2018 & 2019). This research uses the CCI30 index to correct for the market, which is the most comprehensive cryptocurrency index consisting of the 30 largest cryptocurrencies considering market capitalization.[13] The equation consists of the previous formula and adjusting this, plus adding a component that corrects underpricing for the market. This component consists of M_1, which reflects the price of the market portfolio at the end of the listing day minus the market portfolio at the start of the listing day, M_0, divided by the market portfolio at the start of the listing day, M_0.

[13] The index can be retrieved from cci30.com (Appendix A, Figure A6).

$$MUP_i = \frac{P_i - O_i}{O_i} - \frac{M_1 - M_0}{M_0} \tag{2}$$

First-day raw returns (RR)

Formula 3 shows the equation for first-day raw returns, RR_i. To calculate the raw returns the listing day closing price, $P_{i,1}$, minus the listing day opening price, $P_{i,0}$, is divided by the listing day opening price, $P_{i,0}$, of the specific selected ICO.

$$RR_i = \frac{P_{i,1} - P_{i,0}}{P_{i,0}} \tag{3}$$

First-day market-corrected returns (MCR)

Formula 4 shows the equation for first-day market-corrected returns, MCR_i. The equation consists of the previous formula and adjusting this, plus adding a component that corrects the first-day raw returns for the market. This component consists of M_1, which reflects the price of the market portfolio at the end of the listing day minus the market portfolio at the start of the day, M_0, divided by the market portfolio at the start of the day, M_0.

$$MCR_i = \frac{P_{i,1} - P_{i,0}}{P_{i,0}} - \frac{M_1 - M_0}{M_0} \tag{4}$$

4.2 Long-term performance measurement

In this research, raw and market-corrected buy-and-hold returns (BHR and MBHR) function as long-term performance measurements (Ritter, 1991). In the formulas, the closing price of the specific holding period replaces the closing price of the first day. In this research, this will be the closing price after one day, one week, one month, three months, six months, one year, two years, and three years. When extending the time-frame to 4 years or longer, the remaining amount of ICOs in the testing sample becomes too small, so this research will not include this.

Buy-and-hold returns (BHR)

Formula 5 shows the equation for raw buy-and-hold returns, BHR_i. To calculate the buy-and-hold returns the trading day closing price, $P_{i,\alpha}$, minus the listing day opening price, $P_{i,0}$, is divided by the listing day opening price, $P_{i,0}$, of the specific selected ICO. In this case, the specific trading day could vary from one day of trading, one week, one month, three months, six months, one year, two years, or three years.

$$BHR_i = \frac{P_{i,\alpha} - P_{i,0}}{P_{i,0}} \tag{5}$$

Market-corrected buy-and-hold returns (MBHR)

Formula 4 shows the equation for first-day market-corrected returns, $MBHR_i$. The equation consists of the previous formula and adjusting this, plus adding a component that corrects the first-day raw returns for the market. This component consists of M_i, which reflects the price of the market portfolio at the end of the trading day minus the market portfolio at the start of that trading day, M_0, divided by the market portfolio at the start of that trading day, M_0.

$$MBHR_i = \frac{P_{i,\alpha} - P_{i,0}}{P_{i,0}} - \frac{M_i - M_0}{M_0} \tag{6}$$

The outcomes of the formulas; UP_i. MUP_i, RR_i, MCR_i BHR_i and $MBHR_i$ translate into a regression analysis in the next section.

4.3 Regression analysis

To show short-term and long-term ex-post performance, and its relationship to the independent variables, an OLS regression can be run. To show the relationship between short-term performance (underpricing, the 1st day raw and the market corrected buy-and-hold returns) and long-term performance (raw and market-corrected buy-and-hold returns) with the independent variables this study does a regression analysis. Below the equation is given.

$$P_i = \alpha + \beta_1 * tradingvolume + \beta_2 * issuesize + \beta_3 * offerprice + \beta_4 * qualityrating + \beta_5 * marketsentiment + \beta_6 * fundingtargetreached + \beta_7 * retainedpercentage + \beta_8 * category + \beta_9 * country + \beta_{10} * platform + \beta_{11} * hotissuemarket + \beta_{12} * preico + \beta_{13} * currency + \beta_{14} * bonusscheme + \varepsilon$$

The dependent variable is P_i, which indicates the performance measurement. P_i can either be underpricing, market-corrected underpricing, raw buy-and-hold returns or market-corrected buy-and-hold returns. The natural logarithm is taken for all the dependent variables in the regressions ran. The variable its parameter is reflected by β_i and shows to what extent it influences the dependent variable. The total regression includes 14 different variables, which the previous section explains, and an error term, ε.

First, I will run an OLS regression. To start with a conservative method for treating negative values in my dependent variables, I detect the lowest negative value and add this to all outcomes in that specific dependent variable. The lowest single underpricing value was -1, which resulted in me adding a value of 1.1 to every underpricing outcome per ICO. After finalizing this, I conduct a log transformation on all dependent variables.

Second, I did a Cooks D test based on the regression with underpricing as the dependent variable. The Cooks D identifies outliers based on this regression. The test detects the outliers by estimating a value of 4/n and erases the data points with a value higher than this. This test resulted in 22 observations being dropped out of the sample of 263, ending with a final sample of 241. Deleting these influential outliers causes the regression to be more precise. A limitation of regressions, including different dependent variables, changing over time is that it does not detect and erase the correct outliers for long-term buy-and-hold returns (week one – year three). The Cooks D test uses a single regression in this research. However, considering consistency doing the Cooks D test once and continue working with this sample is the most accurate way.

After erasing the outliers and constructing the final sample, I conduct validity tests. First, testing for the existence of heteroskedasticity by doing a Breusch-Pagan / Cook-Weisberg test and a White test to see if the change of the errors is constant, which will be constant if there is homoskedasticity. The results show that the null-hypotheses is soundly rejected for homoskedasticity, meaning that heteroskedasticity is not assumed. Second, I perform a Variance Inflation Factor (VIF) test for multicollinearity. This test shows the variance quotient of a regression coefficient, which allows examining the degree of multicollinearity in the model. The rule of thumb for this test is if the VIF factor is greater than 10, the model has a high level of multicollinearity. In this research, this is not the case. Furthermore, Appendix B includes a correlation matrix (Table B2). The matrix shows that there is no significant correlation between the independent variables. Besides the previous tests, a Ramsey Regression Equation Specification Error Test (RESET) test can be of good use to see whether there are combinations of fitted values that are nonlinear, and this could help to explain the response variable. The models in this research do show this, and they do not have any omitted variables. Finally, I test if the models become more robust by performing robust regressions, but the models do not become more robust. Consequently, I will not use robust regressions.

The next section explains how and when the data is obtained and used. Within ICO research, there are no certified, common-used, and academically accepted databases, which can be addressed and used in ICO research. Moreover, it shows and interprets the summary statistics.

5. Data

This section considers the data and the descriptive statistics. Due to the lack of a general database, this research uses its own database. The next section describes this process of constructing this database. The second section defines and explains the descriptive statistics.

5.1 ICO data

In this section, the data used in this research is both defined and explained. First, one initial dataset had to be built, which consists of as many ICOs possible for the longest possible time-frame obtained from CMC. This is a source that provides token data on daily pricing (open- and closing prices), daily high- and low prices, the trading volume, and the market capitalization. I obtained data from this database by building a web scraper with Python[14]. This time-consuming process resulted in more than one million lines of data, including the initial sample of 2,321 ICOs. This research uses the second-largest initial sample compared to similar ICO research.[15] Furthermore, I use the longest possible time-frame ranging from the 28th of April 2013 (the first date on CMC) up to the 1st of November 2019. Previous research constructed datasets consisting of final samples, including 253 campaigns (Adhami et al.,

[14] Python is a programming language that has multiple features (e.g. developing applications). In this case, Python was used to scrape data from the CMC website in a CSV-file.
[15] Benedetti and Kostovetsky (2018) created a dataset consisting of 2,390 executed and planned ICOs. For now, this is the only research, which used a slightly larger initial sample. However, it could be that there are other papers, which I have not read that use larger samples.

2018), 279 ICOs (Felix & von Eije, 2019), 630 ICOs (de Jong et al., 2018) and 2,390 (Benedetti & Kostovetsky, 2018). Respectively with time-frames of 2014 to August 2017, April 2013 to January 2018, August 2015 to December 2017 and 2013 up to April 2018.

Second, I link CMC data to data from ICObench, ICOdrops, Cryptocompare, reports from other websites, and various coin exchanges. This link is essential as CMC data is limited and only offers data to measure raw buy-and-hold returns. Multiple other variables also have to be taken into account to test ICO performance. Due to the use of different data sources and data transformations, the dataset drops to 629 ICOs. After checking for missing information and when there was no complete overlap between sources the sample dropped to 263.[16] Furthermore, previous IPO research (Ritter, 1991; Loughran & Ritter, 1995; Chan et al., 2001) and ICO research (Momtaz, 2019) have shown that taking a time-frame of three years after an ICO is reliable. Besides, the sample of the regression analysis shrinks over the years. The amount of active ICOs after four years or longer is considerably lower, and this results in not investigating a longer time-frame than three years.

Lastly, to calculate the buy-and-hold returns, the closing price of the specific holding period replaces the closing price of the first day. To obtain more robust results, the returns should be market-corrected, using a benchmark. Using a benchmark ensures that risk mismeasurement is not possible (Ritter, 1991). It could either be market-corrected returns or the Fama-French three factors adjusted returns (Fama & French, 1992) depending on the stock's long-term performance. However, in case the performance is at least as good for IPO stocks as for non-IPO firms, it does not matter which benchmark you choose (Chan et al., 2001). Within ICO research there is a use of either the cryptocurrencies index (CCI30), as a market-corrected benchmark (Felix & von Eije, 2019), or a market capitalization-weighted benchmark (Momtaz, 2019). In this research, the CCI30 is of preference, as this uses the most cryptocurrencies to create an index. The variable market sentiment incorporates this, and the next section describes this.

5.2 Descriptive statistics

Table 2 presents the summary statistics of the regression analyses. The left column shows the variables of the analyses, starting with the 18 dependent variables, followed by the 14 independent variables. The second column shows the amount of ICOs for that regression. The next three columns show the mean, median, and standard deviation. The last two columns

[16] The inaccuracy and limited amount of ICO data is a limitation of this research, which I am aware of.

provide the minimum value and the maximum values of the variable. Both trading volume and issue size are log-transformed. It is interesting to see the trend of the means of the raw buy-and-hold returns (Appendix A, figure A5). The mean returns show an upward trend from the 1st day of trading up to 6 months, but a drop hereafter. After one year, there is a considerable decrease, showing an average buy-and-hold return of 2.74 times to 1.12 times. After two years, there is a decrease, reflecting the consequences of the cryptocurrency crash after the peak on 7 January 2018. After three years, there is a slight increase as almost half of the ICOs, incorporating negative returns in the sample, have perished. The market-corrected buy-and-hold returns show negative means visualizing a run-up to the crash. Furthermore, the average amount of underpricing is 126 percent and slightly decreases when underpricing is corrected for the market.

The initial offer price varies from $0.001 to $31 per token. Furthermore, the quality rating that a token could obtain is between 1 and 5; the data shows that the minimum is 1.1 and the maximum 4.8 in this sample. Moreover, the variable market sentiment is, on average, accounts for an adjustment of 2.2 percent. The funding target reached, is on average, almost 80 percent, and has a maximum of 1020 percent. The average retained percentage is 45 percent. Furthermore, the last variables reflect different categories, countries, platforms, and the values of the four dummy variables.

Table 2: Descriptive Statistics

This table presents the summary statistics of the determinants of short-term and long-term ICO performance. Short-term: UP, MUP, BHR1 and MBHR1. Long-term: BHR2-8 and MBHR2-8. The left column shows the variable name and next to this the amount of observations is shown (N). The Mean is the average and the median is the value of the exact middle observation. Std. Dev. reflects the standard deviation and Min and Max the minimum and maximum values.

Variables	**N**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
UP	241	1.26	0.44	0.90	-2.02	3.03
MUP	241	1.24	0.41	0.92	-2.63	3.03
BHR1	241	0.14	0.05	0.25	-1.03	1.31
BHR2	241	0.37	-0.01	0.60	-1.25	3.13
BHR3	241	1.23	-0.07	0.92	-1.53	4.66
BHR4	241	1.50	0.05	1.13	-1.98	3.37
BHR5	241	2.74	-0.12	1.38	-2.14	4.74
BHR6	239	1.12	-0.74	1.36	-2.28	4.72
BHR7	234	0.61	-0.88	1.09	-2.30	5.53
BHR8	128	0.88	-0.79	1.13	-2.30	5.16
MBHR1	241	0.12	0.04	0.25	-1.03	1.31
MBHR2	241	0.30	-0.04	0.60	-1.25	3.13
MBHR3	241	0.77	-0.25	0.92	-1.53	4.66
MBHR4	241	-0.17	-0.75	1.13	-1.98	3.37
MBHR5	241	-1.75	-3.15	1.38	-2.14	4.74
MBHR6	239	-19.94	-13.84	1.36	-2.28	4.72
MBHR7	234	-61.49	-46.61	1.09	-2.30	5.53
MBHR8	128	0.88	-0.79	1.13	-2.30	5.16
Trading Volume	241	9.49	9.38	3.71	4.29	18.19
Issue Size	241	16.73	16.88	1.50	9.68	20.61
Offer Price	241	1.02	0.20	3.39	0.00	32.00
Quality Rating	241	3.44	3.60	0.77	1.10	4.80
Market Sentiment	241	0.02	0.02	0.05	-0.18	0.19
Funding Target Reached	241	0.79	0.69	1.09	0.00	10.20
Retained Percentage	241	0.45	0.48	0.24	0.00	1.00
Category	241	16.92	-	9.18	1	33
Country	241	30.60	-	12.61	1	46
Platform	241	5.80	-	3.15	2	20
Hot Issue Market	241	0.76	-	0.43	0	1
Pre-ICO	241	0.37	-	0.48	0	1
Currency	241	0.14	-	0.34	0	1
Bonus scheme	241	1.26	0.44	0.90	-2.02	3.03

The next section will include the variables mentioned above into multiple regressions. The results will show what influence they have on the dependent variables. The first section explains the distribution results, the second section interprets the results for the raw buy-and-hold returns, and the third section does the same for market-corrected buy-and-hold returns.

6. Results

This section presents the distribution results and regression analyses. First, Table 3 shows the distribution results of the dependent variables. Second, Table 4 shows the results for the regression analysis of raw buy-and-hold returns. Third, in section 6.3, the results for the market-corrected buy-and-hold returns from Table 5 are interpreted and discussed. In each section, I will first discuss the results from a short-term performance perspective and continue with the long-term performance perspective. Furthermore, in sections 6.2 and 6.3, the control variables will be briefly discussed both for raw and market-corrected buy-and-hold returns.

6.1 Distribution results

Table 3 below shows the distribution results for the dependent variables. The first column displays that there is an average level of underpricing of 126 percent, which is slightly lower when corrected for the market (124 percent). The following two columns present the average raw, and market-corrected buy-and-hold returns. Both show a positive return on the first day, respectively 14 percent, and 12 percent. Furthermore, I conduct a t-test and a Wilcoxon signed-rank test to check for robustness. These tests show significant results for underpricing and first-day returns, which means that these are not affected. Taken this into account, I can reject the first null hypothesis both from a raw as well as a market-corrected perspective.

Long-term ICO performance is reflected in the buy-and-hold returns after a week to three years after investing in ICOs. The previous section discusses the trend for both the average raw and market-corrected returns. This shows positive average raw returns during the whole period. The raw returns show an upward trend where market-corrected returns become negative after three months. Besides, nearly all medians are negative, except BHR1, BHR3 and MBHR4. The results demonstrate that, on average more money is lost over the years than obtained through investing in ICOs. Furthermore, there were positive average ICO raw buy-and-hold returns for the whole period. However, the average ICO market-corrected returns are negative. During the first month and after three years, when almost half of the tokens perished, the average returns were positive. However, negative means were more abundant. Consequently, this means that I can reject the second null hypothesis. Moreover, the tests show no significance for the t-test for MBH4 and MBHR8 and the Wilcoxon signed-rank test for MBHR2. These are all three market-corrected variables and are insignificant due to the market-correction. However, this will not influence the outcomes of the hypotheses.

Table 3: Panel A – Distribution results raw dependent variables

*This table presents the distribution results for the dependent variables. The left column shows the variable of the statistics. To the right, the table displays the dependent variables and the values of the statistics. From left to right, the table shows the corresponding amount of days that belong to the specific dependent variables. Numbers marked with a ***, **, or * represent whether this variable has a significance level of 1%, 5%, or 10%, respectively.*

Dependent Variable	**UP**	**BHR1**	**BHR2**	**BHR3**	**BHR4**	**BHR5**	**BHR6**	**BHR7**	**BHR8**
Benchmark	-	-	-	-	-	-	-	-	-
Days	1	1	7	30	90	180	360	720	1080
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Mean	1.26	0.14	0.37	1.23	1.50	2.74	1.12	0.61	0.88
Median	0.44	0.05	-0.01	-0.07	0.05	-0.12	-0.74	-0.88	-0.79
Standard deviation	0.90	0.25	0.60	0.92	1.13	1.38	1.36	1.09	1.13
Minimum	-0.97	-0.74	-0.81	-0.88	-0.96	-0.98	-0.99	-0.99	-0.99
Maximum	19.63	2.60	21.79	104.71	27.94	113.84	111.32	250.73	172.78
Skewness	3.30	2.77	8.20	12.62	3.22	7.56	9.57	14.96	11.08
Kurtosis	18.94	16.03	91.28	179.92	15.87	69.11	107.67	226.92	124.53
T-statistic	7.77***	6.09***	3.24***	2.66***	5.93***	3.82***	1.93***	0.562***	0.65***
Sign test	0.00***	0.00***	0.04**	0.03***	0.00***	0.00***	0.00***	0.00***	0.00***
Observations	241	241	241	241	241	241	239	234	128

Table 3: Panel B – Distribution results market-corrected dependent variables

*This table presents the distribution results for the dependent variables. The left column shows the variable of the statistics. To the right, the table displays the dependent variables and the values of the statistics. From left to right, the table shows the corresponding amount of days that belong to the specific dependent variables. Numbers marked with a ***, **, or * represent whether this variable has a significance level of 1%, 5%, or 10%, respectively.*

Dependent Variable	**MUP**	**MBHR1**	**MBHR2**	**MBHR3**	**MBHR4**	**MBHR5**	**MBHR6**	**MBHR7**	**MBHR8**
Benchmark	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30
Days	1	1	7	30	90	180	360	720	1080
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Mean	1.24	0.12	0.30	0.77	-0.17	-1.75	-19.94	-61.49	0.88
Median	0.41	0.04	-0.04	-0.25	-0.75	-3.15	-13.84	-46.61	-0.79
Standard deviation	0.92	0.25	0.60	0.92	1.13	1.38	1.36	1.09	1.13
Minimum	-1.03	-0.77	-0.90	-2.36	-7.94	-13.47	-65.72	-174.86	-0.99
Maximum	19.63	2.57	21.70	103.68	27.72	106.68	103.59	225.33	172.78
Skewness	3.30	2.79	8.23	12.52	2.14	6.58	0.53	0.10	11.08
Kurtosis	18.96	15.82	91.87	177.52	10.31	58.14	8.27	7.49	124.53
T-statistic	7.64***	5.12***	2.63***	1.66*	-0.548	-2.40**	-14.84***	-19.45***	0.65
Sign test	0.00***	0.00***	0.548	0.07*	0.00***	0.00***	0.00***	0.00***	0.00***
Observations	241	241	241	241	241	241	239	234	128

6.2 Raw buy-and-hold returns regression analysis

Table 4 provides the results drawn from the regression analyses considering raw buy-and-hold returns. The first row of the table presents the results for the nine dependent variables. The coefficients (shown under *Coeff.*) of trading volume and issue size represent a percentage change of these independent variables explaining a percentage change in the specific dependent variable. The reason for this is that this research takes logged values for these variables. For the other independent variables, the coefficient shows an absolute change reflecting a percentage change in the specific dependent variable. Finally, in the last two rows, the amount of ICOs and the R-squared of the analyses are presented. The R-squared is quite low for all the analyses.

The first independent variable is trading volume, and it demonstrates a 1 percent significance level for UP with a positive coefficient. This is in line with results obtained from traditional IPO literature (Beatty & Ritter, 1986; Miller & Reilly, 1987; Schultz & Zaman, 1994). However, for the analyses hereafter, no significant results can be obtained. From a short-term perspective, trading volume has a positive impact on UP and limited negative influence on the first-day buy-and-hold returns.

The second independent variable is issue size, and it demonstrates multiple significance levels (BHR2-BHR6) with negative coefficients. The empirical regularity (Ritter, 1985; Beatty & Ritter, 1986) for IPOs leads to the assumption that larger ICO issues contain more information, causing issue size to have a positive relationship on performance in the long-term. However, the results show that issue size has a negative impact on long-term buy-and-hold returns. A reason for this could be that indeed more information was available for the larger issues. However, due to this, more investors engaged themselves in investing in these tokens while there was still a large amount of ex-ante uncertainty. Consequently, I do not reject the fourth null hypothesis.

Finally, the control variables included in these analyses show some significance. The offer price and quality rating show varying positive and negative coefficients but are not significant. Market sentiment shows positive signs for up to BHR3, but negative signs afterward. BHR6 and BHR7 have highly negative and significant coefficients (10 percent and 5 percent), reflecting the impact of the cryptocurrency crash in January 2018. The funding target reached has no significant results, while the retained percentage does show some significant results. This reflects that a retained percentage of the tokens, which is not offered, always has a negative effect on the performance of the token. What category the token belongs to shows a significant positive coefficient for UP and a negative coefficient for BHR2. In what country the company does an ICO and on what platform does not show any significant results. Moreover, there are four dummy variables included in these analyses showing some interesting results. The variable hot issue market shows a negative coefficient and is significant, reflecting that UP is lower in situations when more ICOs become completed. In the short-term, it shows significant positive coefficients. However, after the crash between BHR4 and BHR5, it shows large negative coefficients, which are significant for the 1 percent level. The switch from a positive to a negative sign is interesting as this also reflects the cryptocurrency crash. If the offering had a pre-ICO, it has a positive effect on underpricing as well as BHR2 and BHR3. When the token is a currency, this has a significant positive impact on both underpricing and BHR1. The last dummy variable, bonus scheme, shows significant negative results in the long-term (BHR5-BHR8) when the ICO includes a bonus scheme. Lastly, the constant shows what the value will be of the dependent variable in case all independent variables would be zero. BHR2 up to BHR6 have positive values and are significant.

Closing, trading volume has a positive and significant effect on underpricing, but not for the buy-and-hold returns. Issue size has a negative effect on both underpricing and buy-and-hold returns, where the hypothesis states a positive impact. The two main variables of focus show some significance, but the control variables show interesting results, which could also explain variance in underpricing and buy-and-hold returns. The next section while shine light on the market-corrected analyses.

Table 4: Results of raw buy-and-hold returns

*This table presents the raw buy-and-hold returns of the ICO. The left column shows the variable name of the independent variables. To the right, the table displays the dependent variables and the influence of the corresponding independent variables on the dependent variables. From left to right, the table shows the corresponding amount of days that belong to the specific dependent variables. Numbers marked with a ***, **, or * represent whether this variable has a significance level of 1%, 5%, or 10%, respectively.*

Variables	**UP**	**BHR1**	**BHR2**	**BHR3**	**BHR4**	**BHR5**	**BHR6**	**BHR7**	**BHR8**
Benchmark	-	-	-	-	-	-	-	-	-
Days	1	1	7	30	90	180	360	720	1080
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Trading Volume	0.06***	-0.00	-0.00	-0.01	-0.01	-0.01	-0.02	-0.01	-0.00
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Issue Size	-0.04	-0.01	-0.06*	-0.09**	-0.14**	-0.12*	-0.10*	-0.03	0.01
	(0.04)	(0.01)	(0.03)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.08)
Offer Price	0.00	0.00	0.00	-0.00	-0.01	-0.02	-0.01	-0.02	-0.02
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Quality Rating	0.02	0.02	-0.02	-0.04	0.04	-0.03	0.02	-0.06	-0.12
	(0.08)	(0.02)	(0.05)	(0.08)	(0.10)	(0.12)	(0.11)	(0.09)	(0.13)
Market Sentiment	0.74	0.27	1.21	0.84	-0.80	-1.71	-2.79*	-3.07**	-3.38
	(1.07)	(0.33)	(0.76)	(1.18)	(1.46)	(1.69)	(1.53)	(1.32)	(2.42)
Funding Target Reached	0.04	-0.01	0.03	0.08	-0.01	0.03	0.02	0.06	0.00
	(0.05)	(0.02)	(0.04)	(0.06)	(0.07)	(0.08)	(0.07)	(0.06)	(0.08)
Retained Percentage	-0.19	-0.18**	-0.29*	-0.15	-0.60*	-0.65*	-0.62*	-0.49	-0.51
	(0.24)	(0.07)	(0.17)	(0.27)	(0.33)	(0.38)	(0.35)	(0.31)	(0.43)
Category	0.02**	0.00	-0.01*	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Country	0.01	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Platform	0.00	0.00	0.00	-0.01	0.01	0.02	-0.01	-0.02	-0.01
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Hot Issue Market	-0.35**	0.09**	0.17*	0.09	-0.03	-0.78***	-1.31***	-0.79***	-0.40*
	(0.15)	(0.04)	(0.10)	(0.16)	(0.20)	(0.23)	(0.21)	(0.18)	(0.23)
Pre-ICO	0.21*	0.02	0.16*	0.34**	0.04	0.00	-0.11	0.01	0.02
	(0.12)	(0.04)	(0.09)	(0.13)	(0.16)	(0.19)	(0.17)	(0.15)	(0.26)
Currency	0.60***	0.09*	-0.14	-0.07	0.03	-0.20	0.06	0.02	0.05
	(0.17)	(0.05)	(0.12)	(0.19)	(0.24)	(0.27)	(0.25)	(0.22)	(0.32)
Bonus Scheme	-0.05	-0.02	-0.08	-0.15	-0.25	-0.34*	-0.36*	-0.34**	-0.51*
	(0.13)	(0.04)	(0.09)	(0.14)	(0.18)	(0.20)	(0.18)	(0.16)	(0.27)
Constant	0.17	0.28	1.09**	1.98**	3.15***	3.60***	2.89***	0.85	0.00
	(0.74)	(0.22)	(0.52)	(0.81)	(1.00)	(1.16)	(1.05)	(0.90)	(1.39)
Observations	241	241	241	241	241	241	239	234	128
R-squared	0.19	0.07	0.08	0.07	0.06	0.15	0.29	0.20	0.13

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6.3 Market-corrected buy-and-hold returns robustness analysis

Table 5 below provides the results drawn from the regression analyses considering market-corrected buy-and-hold returns. These analyses act as a robustness check on the analyses in the previous section. These analyses have less significant results, but the results show less extreme negative values. Similar results are obtained for trading volume and issue size. Correcting for the market confirms some results shown in the previous section, and it gives a more realistic representation of the effect of the independent variables on the dependent variables. Remarkable changes in these analyses are that the most significant values for retained percentage disappear and the significant coefficients for hot issue market change from negative to positive for buy-and-hold returns. The interpretation of coefficients is the same as described in the previous section. Finally, the R-squared is also relatively low in these market-corrected analyses.

The trading volume demonstrates a 1 percent significance level for MUP with a positive coefficient and a limited insignificant positive effect on the first-day buy-and-hold returns. According to this, I reject the third null hypothesis from an underpricing perspective. However, it cannot be rejected from a buy-and-hold return perspective as it is not significant. The issue size demonstrates multiple significance levels (BHR3-BHR5) with negative coefficients. Two dependent variables less showing significance compared to raw buy-and-hold return analysis. The hypothesis states that issue size has a positive effect on performance in the long-term. However, the market-corrected results also show that issue size has a negative impact on long-term buy-and-hold returns. Therefore, I cannot reject the fourth null hypothesis.

Finally, the control variables included in these analyses show some significance. The quality rating has a negative significant coefficient for MBHR8. Remarkably, market sentiment becomes significant at a 5 percent level the first moment the mean becomes negative for market-corrected buy-and-hold returns (Table 3, Panel B). It also shows a 10 percent significance level for MBHR1. Retained percentage only displays significance for MBHR1 at a 5 percent level. What category the token belongs to shows a significant positive coefficient for MUP and a negative coefficient for MBHR2 and MBHR3 Lastly, hot issue market shows a negative and significant coefficient for MUP. In the short-term, it displays a positive and significant coefficient for MBHR1. However, after the crash between MBHR4 and MBHR5, it now shows positive coefficients. These are significant at a 1 percent level and a 10 percent level, respectively. If the offering had a pre-ICO, it has a positive and significant impact on MUP, but a negative effect on MBHR7. When the token is a currency, this has a positive and significant impact on both MUP and BHR1. Bonus scheme shows a significant negative result for MBHR8 when an ICO includes this. Lastly, the constant shows positive and significant values for MBHR3 up to and including MBHR7.

Summarizing, trading volume has a positive and significant impact on market-corrected underpricing, but not on the buy-and-hold returns. Issue size has a negative effect on both market-corrected underpricing and buy-and-hold returns. These two main variables of focus show some significance, but the control variables also show impressive results that could explain variance in underpricing and buy-and-hold returns.

In conclusion, differing significant determinants throughout the paper can be explained by multiple factors. The data itself fluctuates a lot in this relatively young and highly speculative market. Moreover, the sample includes a period in which the market becomes inflated and eventually crashes. Future studies, consisting of a longer time-frame and a more stable, matured market, should give better insights and more consistent significant results. If companies are willing to adopt rules or regulatory mechanisms, as described by Johnson and Li (2019), this will improve future research. This will make it possible for ICOs to become a trustworthy way of funding. Besides, there is not a certain general database that can be used causing every independent research to set up its own database, which often includes the usage of multiple resources. Building an own database forces the creator to choose certain variables at the beginning of the research based on previous literature and research. In this research, this resulted in a set of fourteen dependent variables. Besides, significance levels in variables shift as the successful ICOs remain, and the bad ICOs die. The sample becomes smaller and consists of the successful ICOs only. For the remaining ICOs, other variables become significant, which are variables contributing to long-term ICO success.

Table 5: Results of market-corrected buy-and-hold returns

*This table presents the market-corrected buy-and-hold returns of the ICO. The left column shows the variable name of the independent variables. To the right, the table displays the dependent variables and the influence of the corresponding independent variables on the dependent variables. From left to right, the table shows the corresponding amount of days that belong to the specific dependent variables. Numbers marked with a ***, **, or * represent whether this variable has a significance level of 1%, 5%, or 10%, respectively.*

Variables	**MUP**	**MBHR1**	**MBHR2**	**MBHR3**	**MBHR4**	**MBHR5**	**MBHR6**	**MBHR7**	**MBHR8**
Benchmark	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30	CCI30
Days	1	1	7	30	90	180	360	720	1080
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Trading Volume	0.06***	0.00	0.00	-0.02	-0.01	0.04	0.04	0.02	-0.03
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.09)
Issue Size	-0.05	-0.01	-0.06	-0.12***	-0.08***	-0.22**	-0.16	-0.08	0.08
	(0.04)	(0.01)	(0.04)	(0.03)	(0.03)	(0.11)	(0.11)	(0.11)	(0.23)
Offer Price	0.00	0.01	0.01	0.01	0.00	-0.01	0.02	0.04	-0.04
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.05)	(0.06)	(0.06)	(0.09)
Quality Rating	0.03	0.03	-0.01	0.03	0.07	0.31	-0.12	0.11	-0.88**
	(0.08)	(0.03)	(0.07)	(0.07)	(0.05)	(0.21)	(0.22)	(0.21)	(0.40)
Market Sentiment	-0.18	-0.69*	-0.02	-1.11	-1.68**	-2.86	-5.05	0.66	-3.94
	(1.11)	(0.39)	(1.02)	(0.94)	(0.74)	(3.00)	(3.08)	(3.00)	(7.19)
Funding Target Reached	0.05	-0.02	0.05	0.04	-0.02	-0.06	-0.02	-0.02	0.12
	(0.05)	(0.02)	(0.05)	(0.05)	(0.04)	(0.14)	(0.15)	(0.14)	(0.25)
Retained Percentage	-0.16	-0.20**	-0.36	-0.16	-0.20	-0.01	-1.15	-0.84	-1.32
	(0.25)	(0.09)	(0.23)	(0.21)	(0.17)	(0.68)	(0.71)	(0.69)	(1.29)
Category	0.02**	0.00	-0.01**	-0.01*	-0.01	-0.02	0.03	0.00	-0.05
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)	(0.02)	(0.04)
Country	0.01	0.00	0.01	0.01	0.00	-0.01	-0.01	0.01	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.03)
Platform	0.00	0.00	0.01	-0.01	0.00	0.04	0.00	0.01	-0.33***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.05)	(0.05)	(0.05)	(0.08)
Hot Issue Market	-0.355**	0.11**	0.16	0.18	0.42***	0.79*	-0.49	-0.48	-0.93
	(0.15)	(0.05)	(0.14)	(0.13)	(0.10)	(0.41)	(0.42)	(0.41)	(0.68)
Pre-ICO	0.212*	0.02	0.16	0.23**	-0.04	0.14	0.02	-0.65*	0.38
	(0.12)	(0.04)	(0.11)	(0.11)	(0.08)	(0.34)	(0.35)	(0.34)	(0.77)
Currency	0.61***	0.09	-0.26	-0.19	-0.09	0.03	0.40	-0.92*	0.01
	(0.18)	(0.06)	(0.17)	(0.15)	(0.12)	(0.49)	(0.51)	(0.49)	(0.94)
Bonus Scheme	-0.05	-0.03	-0.07	-0.12	-0.09	-0.10	0.07	0.17	-2.01**
	(0.13)	(0.05)	(0.12)	(0.11)	(0.09)	(0.36)	(0.37)	(0.36)	(0.81)
Constant	0.23	0.13	0.84	2.77***	3.10***	4.11**	7.13***	5.79***	4.07
	(0.76)	(0.27)	(0.70)	(0.65)	(0.51)	(2.05)	(2.11)	(2.05)	(4.13)
Observations	241	241	241	241	241	241	239	234	128
R-squared	0.19	0.07	0.06	0.10	0.13	0.06	0.07	0.07	0.23

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

7. Conclusion

This paper bridges the gap between short-term ICO performance and long-term ICO performance. A comparison between underpricing and buy-and-hold returns, both considered in their raw form and when corrected for the market. Traditional IPO literature combined with the relatively limited amount of ICO literature to test how ICOs perform, including the cryptocurrency crash in January 2018. This paper contributes to further research done on ICOs, which offers room for both variation and improvement to this research.

The data shows that there was average ICO underpricing of 126 percent and average market-corrected ICO underpricing of 124 percent. Furthermore, there was positive average ICO raw first-day returns and negative average ICO market-corrected first-day returns. The values are comparable to previous ICO research (Adhami et al., 2017; Felix & von Eije, 2019; Momtaz, 2018 & 2019). From a long-term performance perspective, the hypotheses state that the raw buy-and-hold returns should be positive, and the market-corrected results should be negative. The average raw buy-and-hold returns were indeed positive. Although, the market-corrected returns were positive during the first month, and after three years when almost half of the tokens perished, on average, the negative values were larger. In conclusion, there is long-term ICO underperformance, considering average market-corrected buy-and-hold returns.

This research includes two regression analyses. The first involves underpricing and raw buy-and-hold returns. The second covers market-corrected underpricing and market-corrected buy-and-hold returns. The two main variables are trading volume as an indicator of short-term performance and issue size for long-term performance. The former shows significance for underpricing, but it does not for buy-and-hold returns. The latter shows significance for some dependent variables over time, but it does not for the total timeframe from 2013 to 2019. This paper hypothesizes that issue size has a positive influence on long-term performance, but the results show a negative impact. Furthermore, other independent variables can measure long-term performance, such as the retained percentage of the offering, whether the market is hot when doing an issue or if a token had a pre-ICO. This paper lights the path for further research into long-term ICO performance, and it confirms results from previous ICO underpricing research.

Altogether, this paper contributes to the limited amount of research done on ICO performance. Some investors did obtain high returns investing in tokens, but this does not confirm that these investors hold more information than others. The cryptocurrency market remains a high-risk investment market, which inflated until the bubble burst. Moreover, the current valuation of the market also remains speculative. This research offers investors, who are either well-informed or not, to see how FinTech, blockchain, and the ICO market developed over the years. Moreover, this paper demonstrates that the performance of a token does not solely rely on speculation, luck, or a solid investment idea. The results show that, on average, there are positive raw and market-corrected buy-and-hold returns that an investor could earn over the last couple of years. However, investors do have to consider many factors before investing in and while holding a portfolio of tokens. For governments and policymakers, this research shows that just by taking trading volume or issue size as a reference point to obtain ICO information is not enough. Blockchain is a distributed ledger technology, which is neither controlled nor owned by a government, institution, or company. However, ICOs do need rules and regulations. This is in line with findings from Johnson and Yi (2019), that show that companies willing to adapt to regulatory mechanisms will make it possible for ICOs to become a reliable way of funding. Furthermore, this will decrease information asymmetry between the company and the investor, increasing the success of ICO fundraising (Lee et al., 2018).

Finally, this research has some limitations and recommendations for future research. First, the sensitivity to the choice of models, but also to the relatively short time-period the market exists. The coming years will show whether the market can mature, and researchers can conduct improved research. Second, this paper includes the cryptocurrency crash. Future results can be different if it does not include the year of the crash or the years before. Furthermore, there is no universal database to address for ICO research. For this research, I addressed multiple resources to construct a database, which is created based on the research I have conducted. This paper can improve both ICO data collection and usage in the future. Having an ICO database to address, which consists of reliable and aligned data, would improve future research. Finally, this research shows the relevance of a KYC process for both the issuer and the investors, which can counteract or even prevent fraud, speculation, and money laundering. When there are strict regulations, the variables in this research could contain more information to explain ICO performance. Felix and von Eije (2019) do state that speculation motivates most investors, not the company information to possess. When governments set regulations, a company must comply with before it can do an ICO, this will limit the amount of ICOs. However, it will decrease the amount of information asymmetry and accordingly increases the number of well-informed investors. In the end, this will improve the ICO process and create a reliable way of funding.

8. Reference list

Adhami, S., Giudici, G., & Martinazzi, S. (2018). Why do businesses go crypto? An empirical analysis of initial coin offerings. Journal of Economics and Business, 100, 64-75. doi.org/10.1016/j.jeconbus.2018.04.001

Akerlof, G. A. (1970). The market for “lemons”: Quality uncertainty and the market mechanism. In Uncertainty in economics. Academic Press, 84(3), 235-251. doi.org/10.1016/B978-0-12-214850-7.50022-X

Beatty, R. P., & Ritter, J. R. (1986). Investment banking, reputation, and the underpricing of initial public offerings. Journal of financial economics, 15(1-2), 213-232. doi.org/10.1016/0304-405X(86)90055-3

Benedetti, H., & Kostovetsky, L. (2018). Digital tulips? Returns to investors in initial coin offerings. Unpublished working paper. doi.org/10.2139/ssrn.3182169

Chi, J., & Padgett, C. (2005). Short-run underpricing and its characteristics in Chinese initial public offering (IPO) markets. Research in International Business and Finance, 19(1), 71-93. doi.org/10.1016/j.ribaf.2004.10.004

Chishti, S., & Barberis, J. (2016). The FinTech book: the financial technology handbook for investors, entrepreneurs and visionaries. John Wiley & Sons.

De Jong, A., Roosenboom, P., & van der Kolk, T. (2018). What Determines Success in Initial Coin Offerings? Unpublished working paper. doi.org/10.2139/ssrn.3250035

Newman, D. (2018). Exploring 5 Trends Driving The Fintech Revolution. Retrieved from: https://www.forbes.com/sites/danielnewman/2018/07/03/exploring-5-trends-driving-the-fintech-revolution/#58c7477812c7

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. the Journal of Finance, 47(2), 427-465. doi.org/10.1111/j.1540-6261.1992.tb04398.x

Felix, T. & von Eije, H. (2019). Underpricing in the Cryptocurrency World: Evidence from Initial Coin Offerings. Managerial Finance, 45(4), 563-578. doi.org/10.1108/MF-06-2018-0281

Hartmann, F., Wang, X., & Lunesu, M. I. (2018). Evaluation of initial cryptoasset offerings: the state of the practice. In 2018 International Workshop on Blockchain Oriented Software Engineering (IWBOSE). IEEE, 33-39. doi.org/10.1109/IWBOSE.2018.8327569

Howell, S. T., Niessner, M., & Yermack, D. (2018). Initial coin offerings: Financing growth with cryptocurrency token sales (No. w24774). National Bureau of Economic Research. doi.org/10.3386/w24774

Ibbotson, R. G., Sindelar, J. L., & Ritter, J. R. (1988). Initial public offerings. Journal of applied corporate finance, 1(2), 37-45. doi.org/10.1111/j.1745-6622.1988.tb00164.x

ICObench. (2018). ICO Market Analysis 2018. https://icobench.com/reports/ICO_Market_Analysis_2018.pdf

Johnson, W. C., & Yi, S. (2019). Governance in the absence of regulation: a study of initial coin offerings. Unpublished working paper. doi.org/10.2139/ssrn.3337096

Lee, J., Li, T., & Shin, D. (2018). The wisdom of crowds and information cascades in FinTech: evidence from initial coin offerings. Unpublished working paper. https://ssrn.com/abstract=3226051

Loughran, T., & Ritter, J. R. (1995). The new issues puzzle. The Journal of finance, 50(1), 23-51. doi.org/10.1111/j.1540-6261.1995.tb05166.x

Loughran, T., & Ritter, J. R. (2002). Why don't issuers get upset about leaving money on the table in IPOs?. The Review of Financial Studies, 15(2), 413-444. doi.org/10.1093/rfs/15.2.413

Menat, R. (2016). Why we're so excited about fintech. The FinTech Book: The Financial Technology Handbook for Investors, Entrepreneurs and Visionaries, 10-12. doi.org/10.1002/9781119218906.ch2

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. The Journal of finance, 32(4), 1151-1168. doi.org/10.1111/j.1540-6261.1977.tb03317.x

Miller, R. E., & Reilly, F. K. (1987). An examination of mispricing, returns, and uncertainty for initial public offerings. Financial Management, 16(2), 33-38. doi.org/10.2307/3666001

Momtaz, P. P. (2018). Initial coin offerings. Unpublished working paper. ssrn.com/abstract=3166709

Momtaz, P. P. (2019). The pricing and performance of cryptocurrency. The European Journal of Finance, 1-14. doi.org/10.1080/1351847X.2019.1647259

Nadler, P., & Guo, Y. (2020). The fair value of a token: How do markets price cryptocurrencies? Research in International Business and Finance, 52, 101108. doi.org/10.1016/j.ribaf.2019.101108

Nakamoto, S., & Bitcoin, A. (2008). A peer-to-peer electronic cash system. https://bitcoin.org/bitcoin.pdf

Purnanandam, A. K., & Swaminathan, B. (2004). Are IPOs really underpriced?. The Review of Financial Studies, 17(3), 811-848. doi.org/10.1093/rfs/hhg055

Ritter, J. R. (1991). The long-run performance of initial public offerings. The journal of finance, 46(1), 3-27. doi.org/10.1111/j.1540-6261.1991.tb03743.x

Ritter, J.R., 1987. The costs of going public. Journal of Financial Economics 19, 269-281. doi.org/10.1016/0304-405X(87)90005-5

Ritter, J.R., 1984. The hot issue market of 1980. Journal of Business 57, 215-240. doi.org/10.1086/296260

Rock, K. (1986). Why new issues are underpriced. Journal of financial economics, 15(1-2), 187-212. doi.org/10.1016/0304-405X(86)90054-1

Shiller, R. J. (1990). Speculative prices and popular models. Journal of Economic perspectives, 4(2), 55-65. 10.1257/jep.4.2.55

Schultz, P. H., & Zaman, M. A. (1994). Aftermarket support and underpricing of initial public offerings. Journal of Financial Economics, 35(2), 199-219. doi.org/10.1016/0304-405X(94)90004-3

Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. Science, 354(6317), 1288-1292. doi.org/10.1126/science.aah5309

The world's most valuable resource is no longer oil, but data. (2017). Retrieved from: https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data.

9. Appendix

A: Figures

Figure A1 – Token Sales, January – August 2018

Kalomeni, M. 2019, November 12. The ICO market is not collapsing. It's maturing.
Retrieved from: Elementus.io – Addressed on: 12 November 2019

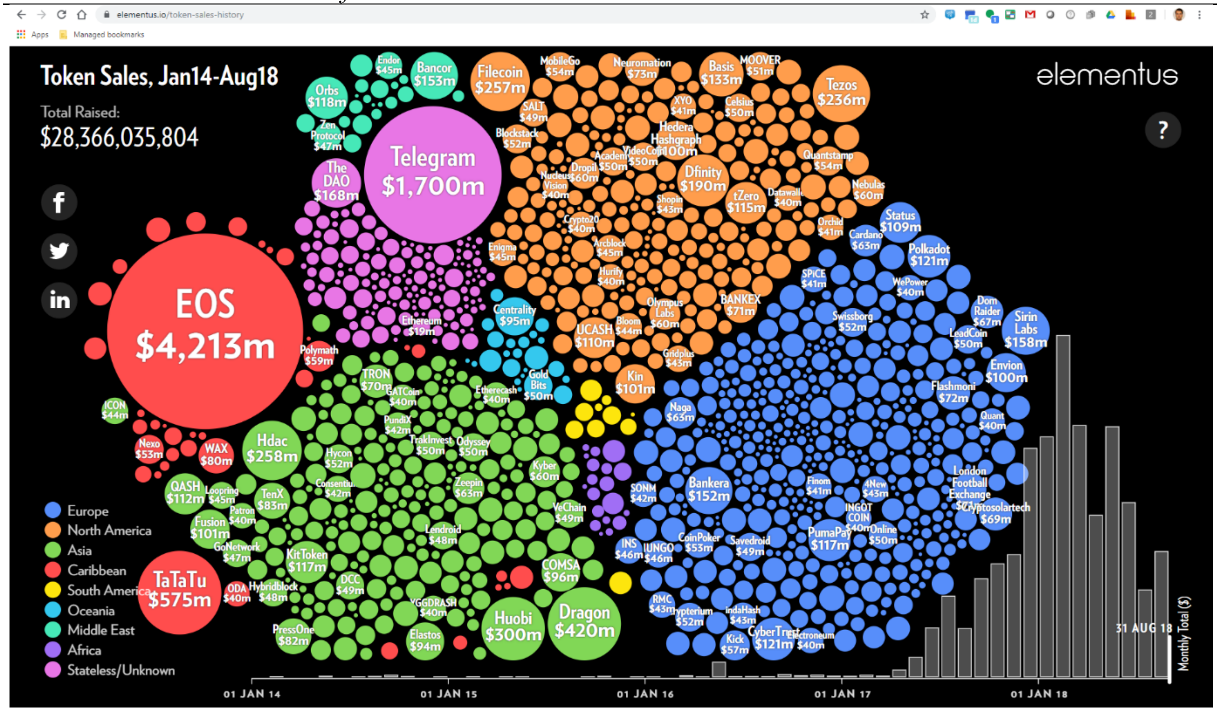

Figure A2 – Figure A4 – Bitcoin Price Development Figures

Etoro.com is a social trading network set-up in January 2007. In 2017 they added cryptocurrency trading to their offering. In 2019 they made an overview of Bitcoin its price development over the years, which they used as an online advertisement. It gives a clear view of this price development.
Retrieved from: Etoro.com – Addressed on: 28 November 2019

Figure A2:

Figure A3:

Figure A4:

Figure A5: Mean Raw Buy-and-Hold Returns

This figure presents the mean percentages of the buy-and-hold returns for the total sample. The graph shows an increasing trend from the 1st day of trading up to 6 months and a drop in returns after 1 year, 2 years and 3 years reflecting the consequences of cryptocurrency crash after the peak at 7 January 2018.

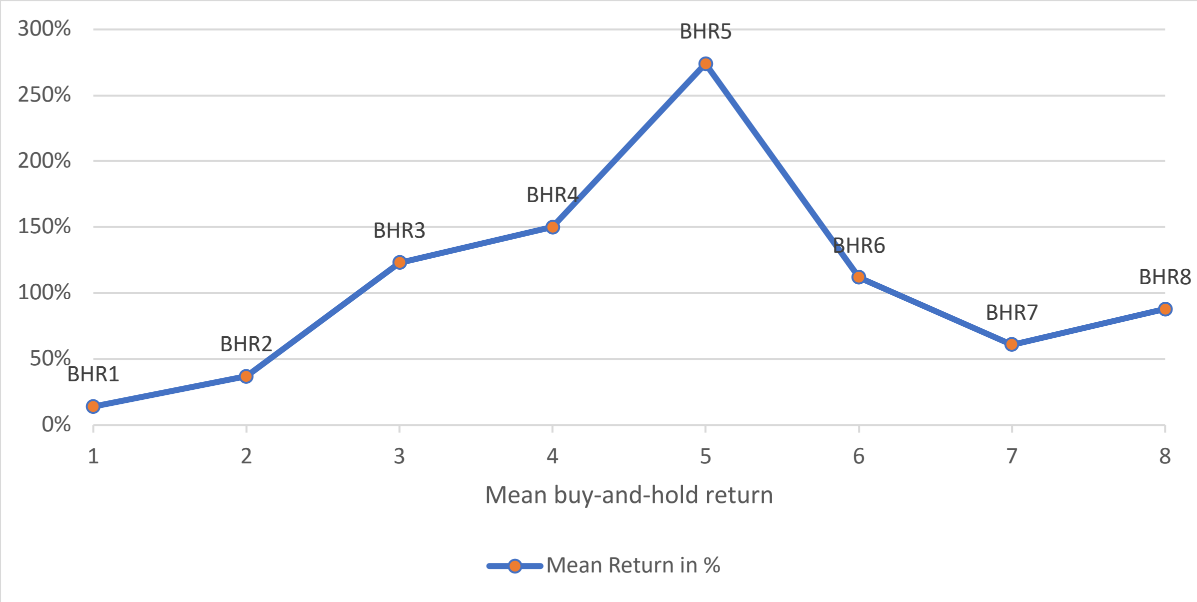

Figure A6: Cryptocurrency Currencies Index (CCI30)

This figure presents the CCI30 index over time (top part). The CCI30 tracks the largest cryptocurrencies by market capitalization and was launched 1 January 2017. The figure also shows the date of the peak 7 January 2018 (see left top corner). Furthermore, the table consist of the total market trading volume over time (bottom part). Cci30.com was addressed on 18 February 2020.

B: Tables

Table B1: Overpricing versus Underpricing with respect to Trading Volume

This table groups overpricing and underpricing and show its corresponding amount of trading volume. The 1st column on the left provides the description. The 2nd column shows the amount of ICOs. The 3rd column shows the total amount of trading volume. The 4th, 5th and 6th columns show respectively the median, the maximum and the minimum.

Description	***Amount ICOs***	***Total Trading Volume***	***Median***	***Maximum***	***Minimum***
Overpricing	88	12.37 million	8899.97	5,914,220.00	43.16
Underpricing	175	655.07 million	11878.20	124,119,000.00	73.20
Percentage (-/+)	50%	2%	75%	5%	59%
Total	263	263	-	2	2

Table B2: Correlation Matrix

This table summarizes the explanatory variables used in the regression analysis. The 1st column on the left provides the variable name. The 2nd column explains what the variable is and its measurement. The 3rd and 4th columns on the right shows the expected sign in the short-term (ST) and long-term (LT)

	UP	**TR**	**IS**	**OP**	**QR**	**MS**	**FTR**	**RP**	**Cat.**	**Cou.**	**Pla.**	**HIM**	**Pre.**	**Cur.**	**BS**
UP	1														
Trading Volume (TR)	0.28	1													
Issue Size (IS)	-0.10	0.07	1												
Offer Price (OP)	0.04	0.09	0.08	1											
Quality Rating (QR)	-0.03	0.08	0.22	-0.04	1										
Market Sentiment (MS)	0.03	0.08	0.03	0.07	0.02	1									
Funding Target Reached (FTR)	0.11	0.07	-0.17	-0.05	-0.06	0.04	1								
Retained Percentage (RP)	0.02	0.08	-0.10	0.19	-0.07	0.11	0.04	1							
Category (Ct.)	0.11	0.01	-0.13	-0.03	-0.07	-0.03	0.07	0.02	1						
Country (Co.)	0.14	0.17	0.03	0.00	-0.07	-0.06	-0.03	0.08	0.04	1					
Platform (Pla.)	0.03	-0.11	-0.17	-0.02	-0.19	-0.03	0.05	-0.05	0.10	0.10	1				
Hot Issue Market (HIM)	-0.19	0.01	0.30	-0.08	0.24	0.08	-0.15	0.06	-0.07	-0.13	-0.11	1			
Pre-ICO (Pre.)	0.05	0.05	0.08	-0.04	0.19	0.06	0.02	0.02	-0.05	-0.12	-0.02	0.31	1		
Currency (Cur.)	0.20	0.12	0.03	0.11	-0.07	-0.04	-0.04	0.15	-0.35	0.03	-0.01	-0.03	-0.01	1	
Bonus Scheme (Bon.)	-0.11	-0.04	0.01	-0.05	0.14	-0.09	-0.14	-0.18	-0.12	-0.15	-0.02	0.22	0.24	-0.13	1