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The effect of launch platforms and blockchain networks on the short-term price performance of cryptocurrency related companies' tokens

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Preface and acknowledgments

I came across the topic of cryptocurrencies when reading the news in 2021, and it instantly caught my attention. Not just because of the amount of hype behind it, but because of the state-of-the-art technology. It spiked my curiosity enough to decide to write my thesis on this topic, combining it with the area of financial economics, which has been my lifelong interest.

This Bachelor's thesis has been written as a conclusion to my International Bachelor of Economics and Business Economics at the Erasmus University Rotterdam. Writing this thesis has been an interesting learning experience both in the field of financial economics and in conducting academic research. For the interested reader, I hope this thesis will be both an educating and a curiosity-inducing read.

I would like to thank dr. Haikun Zhu for his guidance and support during the writing of this thesis. His feedback has at every step of this thesis been crucial and useful. He encouraged me to be creative and maintain sight on the final result, and to write about a topic that interests me.

Abstract

The year 2021 gave rise to cryptocurrencies as potential assets. Cryptocurrencies attracted attention since big profits could be made. This raised the question as to what factors determine the performance of the tokens of companies in the cryptocurrency industry. In this thesis, pertaining to the field of financial economics, the question is to what extent launch platforms, platforms where cryptocurrencies can launch, and blockchain networks, technical infrastructures, affect the performance of cryptocurrencies. Using, the proxies of webpage views and energy consumption, for launch platforms and blockchain networks respectively, in a multiple linear regression, it is found that cryptocurrencies perform statistically and economically better when launching on bigger platforms, and only economically perform better when made on energy efficient blockchain networks.

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Introduction

In August 2021, BitDAO, a decentralized autonomous organization (DAO), which is roughly the cryptocurrency (crypto) industry's equivalent of the stock market industry's shareholder-controlled business, raised over $365 million after launching its token, known by the ticker symbol BIT, on the token launchpad MISO by using a Dutch auction (Genç, 2021). This fundraise was in the crypto news for a long time as it broke a record, it set the record for the largest single initial coin offering (ICO) raise of all time.

The amount of this fundraise is not significant in the stock market industry, which has a record of $25.6 billion, set by Saudi Aramco (Statista, 2022), an amount larger than BitDAO's fundraise in the order of almost a thousand. However, it is significant in an industry that is relatively new and aggressively upcoming. According to Finance Yahoo (2022), the cryptocurrency market reached a value of $1.782 trillion in 2021, and it is expected to grow quickly to $32.420 trillion by 2027, an increase of almost 20 times in six years. Whereas the world stock market has a total market capitalization of over $93.69 trillion in 2020 (The World Bank, 2020). Even though the two industries cannot be compared with each other as the stock market industry is clearly a magnitude larger, the cryptocurrency market is catching up rapidly.

As the cryptocurrency industry has been gaining popularity recently, there are many misconceptions regarding it. Often, cryptocurrencies are compared to currencies. Even though many cryptocurrencies can indeed be used as a currency, like virtually everything, many cryptocurrencies are tokens that represent companies that are in some shape or form involved in blockchain technology. This can be in the area of smart contracts, blockchain gaming, supply chain, or indeed as the name suggests, currencies. In essence, these tokens are tokenized stocks of a regular company. As such, crypto companies often do behave like regular companies, they tend to have a team, founders, and shares, also known as tokens, that can be bought in the form of cryptocurrencies.

These crypto companies can, and are, also valuated, by the team itself when they set the prices for the seed, private, if necessary strategic, and public sales, and these companies are valuated by the market when the tokens are open to trading and the market establishes a price and thus a market capitalization for the company based on both outstanding and total tokens available, indeed like a traditional company on the stock market.

This thesis will dive deeper into the performance and some determinants of crypto companies after its public sale, which is the moment when the general public has the possibility to buy the company's tokens. These public sales of crypto companies are often termed as ICO, IEO (initial exchange offering), or IDO (initial decentralized exchange offering). There are differences between ICOs, IEOs and IDO's, which is mainly the different platform that hosts the public sale. This public sale can be held on one or more centralized exchanges, which are comparable to regular stock market exchanges, for example Binance (centralized exchange) and the New York Stock Exchange (stock market exchange), in which case it is an IEO. A public sale can also be held on the company's website, or launchpads, which exist specifically to launch different crypto companies' tokens, in which case it is known as an ICO or an IDO.

Next to this, these crypto companies' tokens are built on blockchain networks, examples would be the famous Ethereum blockchain network or the Binance Smart Chain network. These blockchain networks differ in their method of operating, and thus can differ quite a bit in speed, scalability, and costs, to name some variables. Hence, distinguishing between blockchain networks is rather important.

To this end, the main research question of this thesis will be:

How do launch platforms and blockchain networks affect the performance of a cryptocurrency company after launching publicly?

This research question will have three sub-questions:

1. How do crypto companies perform after their public launch on the short-term?
2. How do launch platforms affect the short-term performance of crypto companies after their public launch?
3. How do blockchain networks affect the short-term performance of crypto companies after their public launch?

The scientific relevance lies in the fact that the asset class of cryptocurrencies is quite new, and research into crypto companies' public launches is lacking. This thesis contributes to the existing literature in several ways. Firstly, it analyses the short-term performance of crypto companies' public launches in 2021, and as current existing research on this topic is outdated, this thesis aims to deliver a fresh view in this area of research. Secondly, this thesis analyses the effect of launch platforms on the performance of crypto companies after the public sales. And thirdly, this thesis analyses the effect of blockchain networks on the performance of crypto companies after the public sales. Both these last two mentioned areas are rather unresearched, and this thesis hopes to spur further research into this quickly expanding topic and to complement this area of research.

This study is relevant from a social point of view since it can potentially help retail investors as a supportive measure when deciding to invest in a crypto company, to see whether their potential investment is in optimal circumstances, or not. Reversely, crypto companies can look at this thesis as a supportive measure when deciding between launch platforms, and to see whether it is worth it to launch on a more famous platform, or not. Crypto start-ups can look at this thesis to see whether blockchain networks can potentially affect their performance in later stages.

This thesis is organized as follows: The Theoretical framework explains key concepts surrounding the topic of this thesis and looks at current existing research directly related to the topic of this thesis. The Data section includes information on which data is used and the data collection method. The Methodology includes the method and its assumptions used to derive the results. The Results section displays the results that are obtained for the three different sub-questions and discusses the results. Finally, the Discussion and Conclusion critically evaluates the hypotheses and concludes this thesis, while also looking at the limits of this research and suggestions for future research.

Theoretical framework

In this section, key concepts like launch platforms and blockchain networks will be introduced and discussed. Moreover, literature related to the central question and sub-questions will be discussed in the literature review.

Launch platforms

Launching a company is relatively straightforward for an equity-based company, by 'just' listing on an exchange and conducting an Initial Public Offering, known as an IPO. However, doing this on a web-based platform becomes a lot harder. Not only because of the fact that the whole cryptocurrency industry is young and has many critics, but there are different types of platforms to launch on. On the other hand, web-based platforms enabled the phenomenon of cross-border fundraising.

Li and Mann (2018) discuss the implications of an ICO. In a normal ICO, which can take place on the company website, a company raises funds by selling their tokens, which represent their company. These tokens give the investor the ability to use the company's product or service once that is usable. An important difference between an IPO and ICO is that in an ICO investors do not own a share of the company, as opposed to investors in an IPO, who actually buy a part of the company. This raises legal concerns as ICOs do not exactly fit within the established laws of issuing equity, nor laws for protecting the consumers. This gives companies an incentive to hold an ICO, instead of an IPO, as they are confined by fewer laws. However, as Li and Mann establish, this also poses a risk for investors as there are no laws to protect the investors. This is where an Initial Exchange Offering, also known as an IEO, might be more useful.

Takahashi (2019) looked at the difference between an ICO and IEO. A major difference between an ICO and IEO is that in an IEO, like in an IPO for equity-offerings, the exchange makes sure to vet the company, in order to avoid launching scams. The launch takes place on the platform of cryptocurrency exchange, for example Binance or Coinbase.

Miglo (2020) also looked at ICOs and IEOs. He writes in his paper that for investors, an IEO offers the key advantage of having the security that the company they are buying tokens of be vetted. Moreover, an IEO can act as a signalling device for investors. If a company holds an IEO on a reputable exchange, investors might perceive it as the company being of high potential value, as the barriers to entry are high since few projects can hold an IEO, compared to an ICO, due to the vetting by the exchanges.

For the companies themselves, an IEO can not only give the company a badge of credibility, but also broaden their range of potential investors as exchanges usually promote the IEOs that launch on their platform. Next to this, the exchange also manages the whole token sale, thus the company has one task fewer. Moreover, as Georgiev (2022) says in his article, ICO stakeholders also have to worry whether their token will be listed on an exchange, not only is there a listing fee, but they have to worry about competitors. These worries are unfounded when holding an IEO, as listing is all but guaranteed. Miglo concludes his paper by saying that IEOs are better for the company than ICOs.

Then came a new concept, a combination of IEOs and ICOs, the Initial Decentralized Exchange Offering, or IDO. Chitsaz and Bigdeli (2021) researched IDOs in their paper. The main difference between an IDO and IEO is that now the launch platform for the company is not an exchange, but a decentralized exchange. Usually, now there is a third-party that ensures that the decentralized exchange is not a scam. And similarly, the decentralized exchange, also known as launchpads, verify the company as well. After the public sale, the token gets listed on the decentralized exchange.

As Lo and Medda (2020) explain in their paper, a decentralized exchange is essentially a peer-to-peer marketplace, where users can buy and sell tokens. As opposed to traditional exchanges, where the exchange acts as an intermediary between demand and supply, a decentralized exchange makes use of automated algorithms. Considering the fact that one of the main driving points of cryptocurrency is the overabundance of centralization, decentralized exchanges offer the perfect solution to centralization. Another property of a decentralized exchange is the absence of fiat money. Tokens that are bought and sold cannot be traded for traditional fiat money, like the Euro or US Dollar, but instead only for other tokens. Using ‘pools’, the prices of the tokens against other tokens are established. These so called pools contain tokens that users can lock up to earn interest, and the locked up tokens in turn provide liquidity on the decentralized exchange. Moreover, a transaction on a decentralized exchange is put on the blockchain, whereas a centralized exchange only records the transaction on its own servers.

There are many more differences between centralized and decentralized exchanges like privacy, internal risks like vulnerabilities of the blockchain, and external risks like hackers. However, listed are some of the most important ones regarding launching a company.

Blockchain networks

The term 'blockchain' is quickly becoming as mainstream as the internet, with many people calling blockchain technology the next major disruptive technology, much like the internet was back in the mid-1990s (Mougayar, 2016). Blockchain technology creates trust through the use of cryptographic operations, meanwhile it also enables people to safely exchange information without using a middleman. Even though at its centre, blockchain technology only provides a method to safely storing and distributing information, it is the potential use cases of blockchain technology that makes it attract so much attention.

Blockchain technology originates from a crossover between four different fields: Software Engineering, Distributed Computing, Cryptography Science, and Game Theory (Lielacher, 2017). Usually, the applications of blockchain technology are put under the umbrella term 'Cryptoeconomics', which Lielacher defines as: 'A discipline concerned with the production, consumption and transfer of wealth using computer networks, cryptography, and game theory to enhance the prosperity of groups in current and future digital market economies.'

When discussing blockchain, Bitcoin, which popularized blockchain, cannot be ignored. Often considered the father of cryptocurrency, Nakamoto (2008), who introduced Bitcoin in his paper, described the blockchain as a distributed ledger with a sequence of timestamps, which includes the previous timestamp in its hash, which forms a chain of timestamps, and each timestamp that follows reinforces all the timestamps preceding it. However, the aforementioned method is not sufficient to eradicate the double spending problem. The double spending problem is a problem in cryptocurrencies that causes a digital token to be spent twice, or more, because of the fact that a digital token consists of a digital file which can be falsified or replicated (Chohan, 2021). If a blockchain network wants to counter the double spending problem, it needs to form consensus. Nakamoto (2008) introduced a mechanism for this consensus, the Proof-of-Work model.

The Proof-of-Work is a consensus mechanism to decide which participant in the network, also known as miners, are allowed to verify the new data, for which the miners are rewarded a lucrative mining fee. Miners compete with each other to be the first who solves random, complex to solve, but easy to verify the answer of, computational puzzles, hence the name Proof-of-Work. The miner who wins this race is the one who adds the new data to the existing blockchain, and the other miners check the validity of the outcome, thus extending the blockchain (Sultan et al., 2018).

However, the Proof-of-Work consensus mechanism consumes a lot of energy, as many miners are racing to be the first, a lot of computing power that uses electricity is needed. Platt et al. (2021) researched the energy usage of Proof-of-Work compared to other consensus mechanisms, they found that Bitcoin's, which uses Proof-of-Work, energy consumption is higher than all the Proof-of-Stake based blockchains combined by many orders of magnitudes. The energy footprint that Proof-of-Work leaves behind is quite large, hence different consensus mechanisms are more optimal.

Lasla et al. (2020) propose an energy efficient Proof-of-Work mechanism by using a slightly different method. They propose that runners-up are compensated for taking part in the race by giving them the exclusive chance of solving the next problem. This method will reduce the number of miners that participate in a race, and by extension also reduce the amount of energy that is used to extend the blockchain. They write that their idea will consist of two mining rounds per block, in the first everyone can take part and in the second only the runners-up, they estimate that nearly 50% of the energy can be saved.

One of the most famous candidates to eradicate the energy consumption problem is the aforementioned Proof-of-Stake mechanism, which is discussed by Siim (2017). According to Siim, there are two properties because of which a blockchain can function. Firstly, there is some sort of a random process that elects a leader to mine a new block. And secondly, there is a structure that incentivizes miners to participate and not to game the system. Proof-of-Stake is one method that possesses both properties. Namely, a leader that can mine the block is elected based on the amount of currency that it owns, or in other words, the amount of stake the miner has. The more stake a miner has, the higher its chances are to get elected. Moreover, the miners are rewarded a mining fee for their efforts. Unfortunately, as Siim also details, the Proof-of-Stake also has shortcomings like the so called 'Grinding Attack', which enables parties to influence the process of election by coordinating with other parties.

There are many other consensus mechanisms, and each has its benefits and shortcomings. Discussed are two of the most famous and used ones. From the mentioned research, one thing is clear however, energy usage is clearly an important issue as it has been researched by many.

Literature review

Even though the effect of launch platforms on the performance of crypto companies post-launch is rather limited, quite a bit of research has been done on the effect of stock exchanges on the performance of regular companies post-IPO. Ritter (2003) researched recent developments in the European initial public offering (IPO) market. He compared it to the USA IPO market. He found that gross spreads are lower and less clustered than the USA IPO market. His research shows that IPOs launching in USA and Europe launch on different exchanges, hence different circumstances, can differ in post-IPO success.

Nnadi and Bupo (2016) looked at IPOs and their performance during and after the 2008 financial crisis that launched on two different US stock exchanges. Namely, the NASDAQ and the NYSE. They found that during the crisis the NYSE IPOs had an overall higher wealth relative, thus NASDAQ IPOs underperform more than the NYSE IPOs. Moreover, they found that both the NASDAQ and NYSE had a wealth relative under 1, meaning that they both underperform compared to their matching firms.

Lo (2013) looked at the listing and trading competitiveness of stock exchanges in the different continents. Lo made several models with different variables to account for country differences, regulation differences, and exchange differences. Lo found that the different models had several different exchanges at the frontier. She also found that exchanges that have a higher listing competitiveness do not necessarily have more attraction from investors for trading, and also that exchanges that have a higher trading competitiveness do not necessarily have more attraction from companies for listing purposes.

Amira and Muzere (2011) researched competition between stock exchanges for equity. They empirically examined the listing standards of different stock exchanges and the firms' choices of where they decide to cross-list. One of the main conclusions they draw is that companies with a high growth ceiling usually obtain listings on exchanges that have high listing standards.

Luo, Fang and Esqueda (2012) examine the aftermarket performance of Chinese firms in the USA. They look at the period of 1993-2010 and find that Chinese firms that cross list show superior performance relative to Chinese firms that single list in the long run. They conclude that Chinese issuers are motivated to cross-list in the USA due to incentives like over-investment, leverage effects and free-cash-flow signalling. They also found that Chinese firms in the USA underperform their benchmarks three years after the IPO.

Even though the effect of blockchain networks on the performance of crypto companies post-launch has been mostly unresearched, indirectly there has been research on the topic. Xue et al. (2018) examined consensus mechanisms, which all blockchain networks make use of. Because the Proof-of-Work (PoW) mechanism costs a lot of electricity and expensive mining equipment is needed for it, the authors propose a new consensus mechanism, the Proof-of-Contribution. The PoC mechanism is more energy efficient for mining. Moreover, they explore different scenarios in which the PoC is attacked and found that it is more robust than the PoW. The authors propose that the PoC be used instead of PoW.

Zhang and Chan (2020) directly compare the performance of the Proof-of-Work and Proof-of-Stake mechanisms, to see which one might be better. They argue that even though PoS is worse than PoW in terms of fairness, in terms of energy usage PoS is better, and that a mixed mechanism of both the aforementioned mechanisms might compensate the fairness issue of PoS, which arises because of the fundamental stake aspect that some parties have more election chances because they have a larger stake in the network by owning more tokens.

Miraz et al. (2021) discuss alternatives to the old PoW mechanism, which is controversial for its high energy use. They discuss the advantages and disadvantages of many consensus mechanisms, for example, Proof-of-Stake, which is more eco-friendly than PoW, but has disadvantages such as creating a form of centralisation. The Proof-of-Capacity mechanism selects miners based on the amount of disk space that is filled with values made by previous blocks. The Proof-of-Capacity mechanism is, through the use of regular computer resources, not just more eco-friendly, but also more economical for miners, as this method does not require performance enhancing computer parts.

This literature review establishes that there is a link between exchanges and performance of companies, and also a link between consensus mechanisms, thus blockchain networks, and performance of companies through the consumption of electricity. While there is not any research done into the effect of consensus mechanisms, and thus blockchain networks, on company performance after the public sale, the previous research mentioned clearly display that each consensus mechanism can influence the blockchain network, and by extension the company that is built on the blockchain network.

Hypotheses

According to Statista (2022a), the market capitalization of the whole cryptocurrency market on 2 January 2019 was $129 billion, $214 billion on 8 January 2020, and $934 billion on 6 January 2021, eventually rising to its peak of $3.048 trillion on 10 November 2021. Clearly, 2021 was a breakout year for the cryptocurrency industry as a whole, a lot of funds were invested in this industry in 2021, and the industry did well throughout the whole of 2021, as can be seen from the market capitalization through the years. As the whole industry did well in 2021, it is logical that the new companies entering the industry in 2021 were likely to do well too. Hence, the first hypothesis is that in 2021, on average, the crypto companies have positive returns on their public sales.

The second hypothesis is that the more famous a launch platform is, the more successful the crypto companies that launch on that platform are. For this thesis, the proxy for the fame of a launch platform will be the number of views that the launch platform has on their websites. Brettel et al. (2015) researched how, among other things, webpage views affect sales on Facebook. They found that the higher the amount of webpage views there are, the higher the sales are. Thus, if a launch platform has more webpage views, the crypto company that launches on the platform has more exposure to the general public/retail investors. Hence, as this broadens the audience, it is likely that there will be more investors than when a crypto company launches on a lesser known platform as the number of potential investors will be limited. Moreover, the performance of the crypto company is measured in the short-term performance of the crypto company's token over time.

The third hypothesis is that the cost of the blockchain network affects the short-term performance of the crypto company that is built on that specific blockchain network negatively. The cost of the blockchain network is reflected in the usage of electricity for the blockchain network. Sedlmeir et al. (2020) looked at the blockchain technology's consumption of energy. They wrote that the widespread adoption of blockchain technology can be inhibited or delayed if the energy consumption remains problematic due to the effect it will have on sustainability and climate change. Hence, it is likely that there is more adoption of a certain blockchain network if that blockchain network consumes less electricity, or in other words if it is cheaper. If there is more adoption of a blockchain network, there are more potential investors for a crypto company that runs on that blockchain network, and there is likely that that crypto company is more successful.

Data

Main and control variables

To answer the first sub-question and measure the performance of crypto companies after launching, the performance of the company's token, compared to the respective launch price, will be used. The return will be calculated for the performance of the token one week after the launch, two weeks, and three weeks after launch.

To answer the second and third sub-questions and to estimate the effects of launch platforms and blockchains on the performance of new crypto companies, a few proxies will be used. Namely, to measure the effect of launch platforms, the amount of webpage views that the launch platform gets will be used as a proxy. And for blockchains, a measure of electricity usage will be used.

Moreover, a few control variables are included as well. The first control variable is the amount of raise that the company has on the launch platform. And secondly, whether the launch was done in a bull or bear market. Moreover, eleven dummies will be added to control for fixed time effects as well, one for each month and the base case will be January. The eleven dummies will be added to control for changing circumstances over time that stay constant for all the observations, like new innovations in the industry. Thus, the month can affect the raise and can be correlated with the raise amount, webpage views, cycle and blockchain network.

The amount of raise can be positively correlated to the amount of webpage views that a launch platform gets. This can be the case as the launch platforms that get more views tend to be the ones that are more famous, and thus there are more potential investors and the ceiling for the raise amounts are higher. Moreover, the amount of raise can also positively affect the performance after launching as usually the projects with a higher amount of raise can utilize more money for the betterment of the company, thus the raise amount is a good control variable. Leaving out this control variable can lead to positive omitted variable bias.

After the industry became mainstream and more attractive for institutional investors, the launch prices, the raise amounts, and webpage views of the launch platforms, among other things, increased due to the rapid attention the industry gained. However, this was only during the period when tokens were booming and increasing in price, thus profits were to be made. Consistent with theories like Tan and Kim (2016), who found that IPO volumes fluctuate with the situation of the whole market, in times of dire markets, launching becomes less attractive as fewer investors are willing to invest because of a bear market and decreasing prices and profits. This means that a bull cycle can positively affect the performance of crypto companies. Moreover, whether a launch was conducted in a bull market can be positively correlated with the webpage views and the raise amounts, as more webpage views are likely to be observed when there is more attention on the industry. Thus, the bull cycle variable is a necessary control variable, and can lead to positive omitted variable bias if it is not included.

Data sources and collection

To collect the list of public launches that took place in 2021, Coinmarketcap.com will be used. Coinmarketcap is a website that collects and records all things related to cryptocurrencies, it has been used several times by other researchers such as Feder et al. (2018), for example, who used Coinmarketcap to extract price data for their research on the rise and fall of cryptocurrencies. Moreover, by using a data aggregator like Coinmarketcap, we can be sure that the list of projects does not include illegitimate projects. Together with the list of public launches in 2021, data on the launch platform, the blockchain network and the total raise amount is also collected from Coinmarketcap. After collecting this list, all observations that have empty values for any variables are first looked up on the company website, if no information is found, the observation is deleted.

In total there are 496 different public listings that took place in 2021, after removing some observations, 447 observations remain, as can be seen in Table 1 in the previous section. Namely, empty observations and extreme outliers were removed due to inexplainable errors in Yahoo Finance after cross checking with Coinmarketcap. Some companies decide to hold a public launch on multiple exchanges. After considering the companies that have multiple launches, there are a total of 322 different companies. However, for this research all the 447 observations will be used.

After collecting the list of projects that launched in 2021 publicly, Yahoo Finance will be used to collect the price data of the tokens, through the use of the interface that Yahoo Finance provides. The price data will include the weekly prices for all the tokens. However, as there are over 300 different companies, collecting price data for each company can be cumbersome.

Thus, the programming language Python will be used to collect the data. Using the PIP command on the command prompt, the yfinance and pandas packages are installed. Using the yfinance package, data from Yahoo Finance can be fetched. After using the yfinance package, the pandas package can be used to convert the data to Excel for further finetuning. In Excel, the returns are calculated using the public launch prices from Coinmarketcap and the price data from Yahoo Finance. The code used in Python can be found in Figure 3 in the Appendix.

Data for the launch platform variable proxy will be collected from Similarweb, which provides web analytics services. Several researchers have used Similarweb in the past, for example Suksida and Santiworarak (2017) in their paper in which they research the effect of different web analytics measures on impact rankings of webometrics. From Similarweb, the average amount of monthly views in 2021 will be collected for all the launch platforms.

For the proxy of blockchain networks, the results of Bada et al. (2021) will be used. In their paper, they plead for more sustainable blockchain consensus mechanisms by analysing the current existing consensus mechanisms and their energy consumption. They rank the different consensus mechanisms on their energy consumption from 1 to 18, with 1 being the worst rating and 18 being the best rating. As blockchain networks have consensus mechanisms, this ranking will be used as a proxy for the blockchain network variable. The ranking will be applied to the different consensus mechanisms that the blockchain networks use. On the official white paper of the blockchain network, the consensus mechanism that it uses will be looked up.

The public launch dates will be collected from Coinmarketcap, which will identify which dummy variable for the months is recorded as a 1 or 0. Further, to identify whether the token launched in a bull or bear market, the price action of Bitcoin will be used, as it is the market leader in the cryptocurrency industry, and much of the price action of other tokens is quite dependent on Bitcoin, as Kulal (2021) established in his paper. In accordance with the research of Hanna (2018), the bull cycle is defined as an extended period of time when Bitcoin's price is increasing over the year of 2021, which is from 1 January 2021 till 13 April 2021, and 20 July 2021 till 8 November 2021. A bear cycle is defined as a period when Bitcoin's price is decreasing over an extended period of time in 2021, which is from 14 April 2021 till 19 July 2021, and 9 November 2021 till 31 December 2021. In the Appendix can be found Figure 2 which displays the price action of Bitcoin during 2021.

Methodology

For the first sub-question, data on the company performance will be used and processed in Microsoft Excel. The data will be displayed in a boxplot through different moments of measurements of the performance, in essence one, two and three weeks.

For the second and third sub-questions, after collecting the data as mentioned in the previous section, it will be processed in STATA. A multiple linear regression, instead of the simple linear regression as there is more than one independent variable, will be estimated with the use of the ordinary least squares method. The equation of the regression is as follows:

$$\text{Dependent variable} = \alpha + \beta_1 \text{ control variable 1} + \beta_2 \text{ control variable 2} + \beta_3 \text{ dummy 1} + \ldots + \beta_{13} \text{ dummy 11} + \beta_{14} \text{ independent variable 1} + \beta_{15} \text{ independent variable 2} + \epsilon$$

The dependent variable in this regression is the return, which measures how the company's token performs compared to the price of the public launch. This variable is in decimals, and thus continuous. Three regressions will be performed, model 1 for week 1, model 2 for week 2, and model 3 for week 3. Three models will be made because price action can fluctuate shortly after launching.

The first control variable is the market cycle. This variable is a dummy variable and takes the value of either a 0 or 1, depending on whether the observation occurs in a bear market as defined in the previous section or in a bull market, respectively. The second control variable is the token raise amount. The raise amount will be a discrete variable, as it can be any whole number, and in the denomination of US Dollar. The dummies to control for time fixed effects are recorded in either a 0 or 1, with 1 being for the raise being done in that specific month, and the reference category being January.

The first independent variable is the blockchain network. After using the results of Bada et al. (2021), a rating has been applied to the different consensus mechanisms and thus by extension to the blockchain networks. This independent variable will be a discrete and categorical variable, as it can only take on a finite number of values, specifically between 1 and 18.

The second independent, and last, variable in the equation is the launch platform. It will be proxied by the average webpage views that the launch platform gets. This variable is a discrete variable, as the webpage views can be any number.

Now, the equation of the regression is as follows:

$$Ret = \alpha + \beta_1 \text{ cycle} + \beta_2 \text{ raise amount} + \beta_3 \text{ February} + \ldots + \beta_{13} \text{ December} + \beta_{14} \text{ webpage views} + \beta_{15} \text{ consensus mechanism rating} + \epsilon$$

Table 1 Summary statistics for all variables

Variable	Obs.	Mean	Std. dev.	Minimum	Maximum
Return Week 1	447	9.732694	16.44826	-0.7933333	93.226
Return Week 2	447	7.574687	11.78461	-0.78116	79.02355
Return Week 3	447	6.965176	10.98131	-0.8213333	72.69725
Webpage Views	447	$1.51*10^7$	$1.29*10^7$	517	$5.86*10^7$
Rating	447	4.736018	3.126213	1	18
Bull Cycle	447	0.4004474	0.4905381	0	1
Raise Amount	447	569699.1	1424238	15000	$1.20*10^7$
February	447	0.0089485	0.0942781	0	1
March	447	0.0850112	0.2792108	0	1
April	447	0.1029083	0.3041795	0	1
May	447	0.1655481	0.3720909	0	1
June	447	0.0693512	0.2543351	0	1
July	447	0.0559284	0.2300409	0	1
August	447	0.0447427	0.2069702	0	1
September	447	0.0693512	0.2543351	0	1
October	447	0.0961969	0.2951914	0	1
November	447	0.1677852	0.3740941	0	1
December	447	0.1297539	0.336409	0	1

Note. ‘Obs.’ stands for observations. ‘Std. dev.’ stands for standard deviation.

Table 1 contains summary statistics for the variables included in this research. Some noteworthy statistics are the returns, as the lowest return for a company in the third week is -82.13%, which is for a cryptocurrency token named Kommunitas, and the maximum return for a project in the first week is equal to 9322.60%, which is for a cryptocurrency token named Chumbi Valley. Moreover, the highest token raise amount is equal to $12,000,000 USD, which was raised by the company Casper on the launch platform of Coinlist, one of the most famous launch platforms by average monthly webpage views.

Linear regression assumptions

As a linear regression will be performed on the data, it is important to check if the data satisfy the assumptions of a linear regression. According to Tranmer and Elliot (2008) there are five key assumptions that must hold for a linear regression to be valid. In this section the assumptions will be discussed, and the data will be checked to see if it is fit for a linear regression.

The first assumption is that the response variable is continuous. With the dataset in this thesis, the response variable is the return on investment, which is most certainly a continuous variable as it can be any numerical value, with a logical minimum of -1, as returns cannot be less than -100%, or akin to bankruptcy. Thus, the first assumption is not violated.

The second assumption is that the relationship between the response and explanatory variables is linear. In the Appendix can be found Figure 4 and Figure 5, which are two-way scatterplots that plot the relationship between the returns of the three weeks and webpage views, and the returns of the three weeks and ratings. From the plot can be seen that there is no clear evidence for a non-linear, for example quadratic, relationship between the response and explanatory variables. Thus, the second assumption is not violated.

The third assumption is that there is no perfect multicollinearity. This can occur when variables are correlated with each other, and Tabachnick and Fidell (2007) put the threshold at a correlation of 0.9 or higher, however perfect multicollinearity occurs when the correlation is 1. Table 4 displays the correlations between the explanatory variables, and since the highest correlation is equal to 0.39, it can be concluded that there is no perfect multicollinearity present and that the third assumption is also not violated.

The fourth assumption is that the residuals are homoscedastic. To check this, scatterplots of all three models can be found in Figure 6, Figure 7, and Figure 8 in the Appendix to check for homoskedasticity. Heteroskedasticity can be seen to be present in the plots.

However, just to be sure a Breusch-Pagan test is implemented, the results of which are in the Appendix in Table 5. For all three models, strong rejection of homoskedasticity is established, as the p-values are less than 0.0001. This could be driven by outliers, however, as there is no evidence to further suggest that there are mistakes in recording the observations, these outliers cannot be removed further. Autocorrelation is not checked as there are no time series in these regressions. To handle the violation of the fourth assumption of homoskedasticity, the Generalized Least Squares method will be implemented, which uses heteroskedasticity robust standard errors.

The fifth assumption is that the residuals are normally distributed. Figure 9, Figure 10, and Figure 11 show that there are heavy outliers on the right tail for all three weeks, thus there is left skewness. The figures suggest that the distribution of the residuals is not normal. To improve this, the residuals are modelled with a (scaled) log-normal distribution. Next to this, the log-normal distribution is known to be quite applicable to financial data, for example Odhiambo et al. (2020) and Hoffman (1993) use and explain the applicability of the log-normal processes to financial data. A better fit of the residuals can be achieved by using a non-linear model.

The desired regression is:

$y = X\beta + \epsilon, \epsilon \sim Log\ N(\mu, \sigma^2) - 2$. The negative two introduces the correct range of the residuals. As y ranges from negative one, which is bankruptcy, to infinity, however, to introduce a negative penalty for outliers, it is bounded by negative two.

$y + 2 = X\beta + e^{\epsilon}, \epsilon \sim N(\mu, \sigma^2)$. This is by definition of the log-normal distribution.

$y + 2 \approx e^{X\beta + \epsilon}, \epsilon \sim N(\mu, \sigma^2)$. This is by the first order of the Taylor expansion.

$u = \ln(y + 2) = X\beta + \ \epsilon\ ,\ \ \epsilon \sim N(\mu, \sigma^2)$. This is the final equation.

The final equation is a transformation of the dependent variable (Singh, 2022). After applying this transformation to the data, histograms are plotted in Figure 12, Figure 13, and Figure 14 in the Appendix, which show the new residual plots look a lot more normally distributed than before. Thus, the transformation is useful, and the fifth assumption is not violated anymore.

Thus, the final equation is:

$$\text{Ln(Ret)} = \alpha + \beta_1 \text{ cycle} + \beta_2 \text{ raise amount} + \beta_3 \text{ February} + \ldots + \beta_{13} \text{ December} + \beta_{14} \text{ webpage views} + \beta_{15} \text{ consensus mechanism rating} + \epsilon$$

Results

Performance of companies

To answer the first sub-question of how crypto companies perform after their public launches in 2021, the following was hypothesized in the Theoretical framework: In 2021, on average, the crypto companies have positive returns on their public sales.

To be able to answer this sub-question, a boxplot has been created in Excel. Figure 1 portrays the returns in decimals, not percentages, for one, two and three weeks after the public launch of the companies.

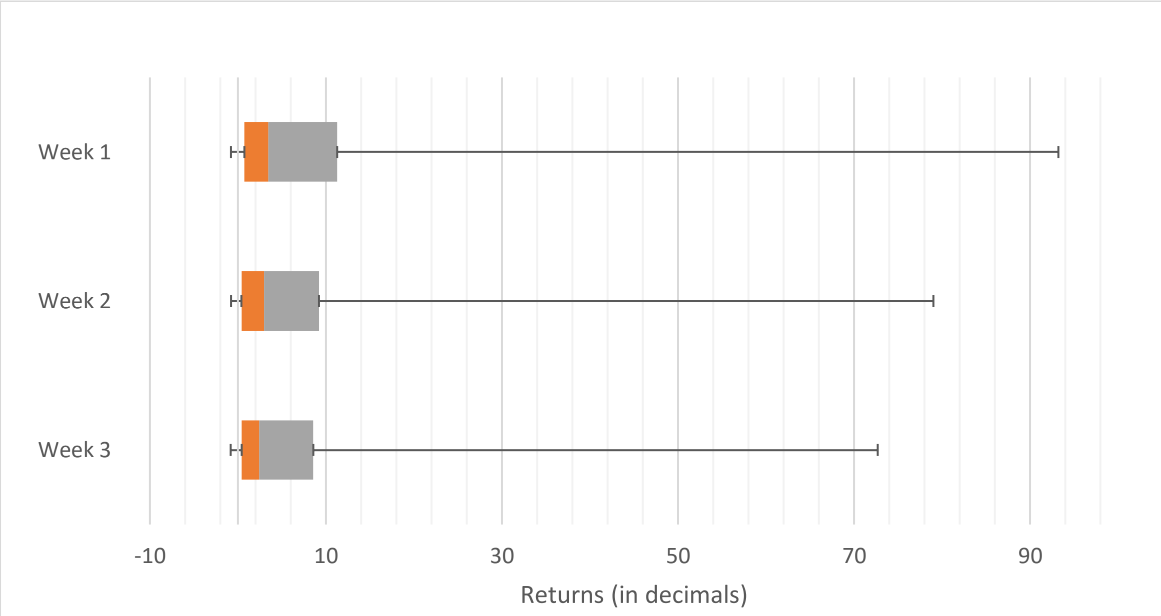

Figure 1 A boxplot of the returns of the public launches in 2021, after one, two, and three weeks

As the figure portrays, the returns of almost all public launches were positive in all the three weeks. A little difficult to see, due to the wide range of spectrum, is that very few public launches were in the negative across all three weeks. The median return of the first, second and third week is 348.45%, 296.09%, and 244.75% respectively. Whereas the average return is equal to 973.27%, 757.47%, and 696.52% for the first, second and third weeks, respectively, as can be seen in Table 1 in the Data section. From both statistics can be seen that generally, for most projects, the returns tend to decrease as time goes on.

From Figure 1 can also be seen that the gap between the top 25% companies and the rest decreases, as the returns of the top quartile keep decreasing over the three weeks. As a matter of fact, all the quartiles decrease over the three week period. Suggesting that through initial price action the returns are high, but as the price action decreases as time goes on, so do the returns decrease.

In general, however, most projects enjoy from solid returns as can be seen from Table 2, which portrays the percentage of projects that have positive and negative returns over all the three weeks after the public launch. As can be seen from Table 2, the overwhelming majority of the crypto companies saw positive returns after launching publicly in all three weeks. However, the percentage of companies that experienced positive returns did decrease as time went on.

From the results of Figure 1 and Table 2 can be concluded that indeed on average, in 2021, crypto companies have positive returns, as hypothesized.

Table 2 The percentage of companies that experienced either positive or negative returns after one, two and three weeks after the public launch, in 2021

	Positive	**Negative**
Week 1	0.899329	0.100671
Week 2	0.852349	0.147651
Week 3	0.838926	0.161074

Launch platforms and blockchain networks

To answer the second and third sub-questions of how the launch platforms and blockchain networks affect the performance of crypto companies, regressions in STATA are performed. The results of these regressions can be found in Table 3. In Table 3, three models are included. In the first model the performance of the crypto companies one week after the public launch is regressed on the independent and control variables, in the second model the performance of the crypto companies after two weeks is regressed on the independent and control variables, and in the third model the performance of the crypto companies after three weeks is regressed upon the independent and control variables.

For the second sub-question, the following was hypothesized previously: The more famous a launch platform is, the more successful the crypto companies that launch on that platform are. The results in Table 3 are in accordance with the hypothesis. All three models show that the amount of average monthly webpage views the launch platform gets in 2021, positively impacts the performance of the crypto companies in the three weeks after the public launch. The coefficients are statistically significant in all three the models at the 10%, 5% and 5% level, for model 1, 2 and 3, respectively. Further, the coefficients are economically significant. On average and keeping all else constant, in 2021, increasing the webpage view count by one, increases the return of crypto companies' tokens by ($100 * (e^{1.39*10^{-9}} - 1) =$) 1.393*10^{-7}% / 1.57*10^{-7}% / 1.48*10^{-7}% after one / two / three week(s), respectively. Similarly, increasing the webpage view count by ten million increases the return of crypto companies' tokens by 1.39% / 1.57% / 1.48% after one / two / three week(s) of launching publicly, on average and keeping the other variables constant.

For the third sub-question, the following was hypothesized in the Theoretical framework: The cost of the blockchain network affects the performance of the crypto company that is built on that specific blockchain network negatively. It is important to remember that the higher the rating, the less the cost of the blockchain network, as was established in the Data section, and that the maximum rating a project can get is 18. From the regression results, it can be concluded that this hypothesis is correct. According to the regression results, the rating is statistically insignificant in all the three weeks, although economically it is significant. On average and keeping all else constant, using a consensus mechanism that is rated higher by 1 increases the returns by $(100 * (e^{0.0105452} - 1) =)$ 1.06% / 1.06% / 0.84% after one / two / three week(s) of launching publicly, respectively.

While the results for the control variables are not completely relevant for the three sub-questions, the results will be quickly discussed. Compared to a bear cycle, when a public launch was held in a bull cycle in 2021, on average and keeping everything else constant, the returns of a company token decreased by $(100 * (e^{-0.0553321} - 1) =)$ 5.4%, and increased by 8.77% and 23.66% after one, two and three weeks of launching publicly, respectively. Although economically significant, this control variable is statistically insignificant in all three models.

The second control variable, the raise amount, is statistically significant in the first and third model, however, it is statistically insignificant in the second model. Keeping everything else constant and on average, increasing the raise amount by 1 USD increases the return of a company's token by $(100 * (e^{4.63*10^{-8}} - 1) =)$ 4.63*10^{-6}% / 3.13*10^{-6}% / 4.34*10^{-6}% after one / two / three weeks of launching publicly. Through a similar analysis, increasing the raise amount by 10 million USD increases the returns of a company's token by 46.3% / 31.3% / 43.4% after one / two / three weeks of launching publicly, keeping all else constant and on average.

Meanwhile, January seems to be the best time to have launched in 2021, as all the dummies for the months are negative. For example, compared to launching in January, launching in February decreases the returns by $(100 * (e^{-1.996475} - 1) =)$ 86.42% / 85.0%, and 85.71%, on average and keeping the rest of the variables constant, after one / two / three weeks of launching publicly, respectively. Important to note is that besides being economically significant, all the dummies for the time fixed effects are statistically significant at the 1% level in all three models.

Next to this, it is noteworthy that even though the R^2, which measures how well the model explains the observed data, is low for all three models, it increases as time goes on. An example to explain the R^2: In the third model the R^2 equals 19%, this means that 19% of the variation of the dependent variable is explained by the independent and control variables. The R^2 would likely increase if more variables are added that explain the dependent variable well.

Table 3 The regression results for the three weeks

	Returns		
Variable	**Week 1**	**Week 2**	**Week 3**
Bull Cycle	-0.0553321	.0837616	.2123453
	(0.1926898)	(.2041419)	(.2108273)
Raise Amount	4.63e-08*	3.13e-08	4.34e-08*
	(2.86e-08)	(2.59e-08)	(2.41e-08)
February	-1.996475***	-1.896863***	-1.945862***
	(.4929253)	(0.4836422)	(.3712972)
March	-1.263136***	-1.251118***	-1.496949***
	(.1624503)	(.1628056)	(.1582981)
April	-1.465585***	-1.422247***	-1.422028***
	(.1997718)	(.2017976)	(.2004366)
May	-1.935594***	-1.944672***	-1.843281***
	(.2369396)	(.2362786)	(.2413765)
June	-2.364522***	-2.163925***	-2.124922***
	(.2362026)	(.2442235)	(.2544102)
July	-2.240758***	-2.073456***	-2.038327***
	(.2250826)	(.236528)	(.2570287)
August	-1.724696***	-1.664655***	-1.796319***
	(.1945708)	(.1961441)	(.1799599)
September	-1.799627***	-1.815671***	-1.889385***
	(.148346)	(.1552732)	(.1547693)
October	-1.148421***	-1.220781***	-1.291483***
	(.1702992)	(.1594148)	(.1659402)
November	-1.198744***	-1.108828***	-1.243567***
	(.2136236)	(.2297791)	(.2359573)
December	-1.930975***	-1.827117***	-1.832124***
	(.2497757)	(.2463112)	(.2506364)
Webpage views	1.39e-09*	1.57e-09**	1.48e-09**
	(8.02e-10)	(7.94e-10)	(7.12e-10)
Rating	.0105452	.0105173	.0083172
	(.0155214)	(.0138141)	(.0134276)
Constant	3.439753***	3.212064***	3.151032***
	(0.1970522)	(0.2086811)	(0.2150268)
Observations	447	447	447
R^2	0.09	0.17	0.19

Note. Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.10.

Discussion and conclusion

In this thesis, the central question was:

How do launch platforms and blockchain networks affect the performance of a cryptocurrency company after launching publicly?

To answer this central question, it was split in three sub-questions with each its own hypothesis with the aim of predicting the answer to the question bearing in mind the research that has already been done.

To answer the first sub-question of how crypto companies' tokens perform on the short-term after their public launch, it was hypothesized that on average the tokens have positive returns on their public launch prices. The regression results in the previous section have shown that this has indeed been the case for almost all the projects. In fact, most of the projects sustained positive returns in the three weeks after launching publicly. The results obtained for the first sub-question are in line with the statistics from Statista (2022a), which indicate that the whole cryptocurrency market had been rising throughout 2021.

For the second sub-question of how launch platforms affect the crypto companies' token prices on the short-term, it was hypothesized that the more famous a launch platform is, the more successful crypto companies that launch on that platform are. The regression results in the previous section clearly showed that the proxy for the launch platforms, the webpage views, is statistically and economically significant, and can positively influence the performance of crypto companies after their public launch. In the Theoretical framework, research surrounding the topic of launch platforms has been discussed. Nnadi and Bupo (2016) researched IPOs and their performance after listing on two different US stock exchanges and found that stocks that listed on NASDAQ after IPO performed worse than stocks that listed on NYSE after their IPO. Meaning that the exchanges can affect the performance post-IPO. Lo (2013) found in his research that significant differences in the aspects of stock exchanges can exist. Moreover, Brettel et al. (2015) researched how webpage views affect sales on Facebook. He found that a higher amount of webpage views leads to more sales. The regression results also indicate that launch platforms can have an effect on the performance of crypto companies after their public launch. The results obtained from the regression are in line with the hypothesis and the research discussed in the Theoretical framework.

For the third sub-question of how blockchain networks affect the crypto companies' token prices on the short-term, it was hypothesized that the cost of the blockchain network negatively affects the short-term performance of the crypto company that is built on that specific blockchain network. The regression results in the previous section showed that the proxy for blockchain networks, the rating as established by Bada et al. (2021), is economically significant, but not statistically significant. As a higher rating is given to more economical blockchain networks, it means that the higher a rating a blockchain network gets, the less its costs are. The results indicate that the costs of the blockchain networks do indeed negatively influence the short-term performance of the crypto companies' token prices. Various research was discussed in the Theoretical framework regarding blockchain networks. Miraz et al. (2021) discussed alternatives to the Proof-of-Work mechanism since it has a high energy usage. Furthermore, Sedlmeir et al. (2020) wrote in their research that the adoption of the blockchain technology can be inhibited or delayed if the high energy consumption problem does not get solved, and that a blockchain network that is more energy efficient is more likely to be utilized than one that is less energy efficient. The results obtained from the regression are in line with the hypothesis and the mentioned literature in the Theoretical framework.

In conclusion, the answer to the central question is this: Launch platforms, measured by their webpage views, can positively influence the performance of the crypto companies' tokens, and the blockchain networks, measured by their electricity consumption, can negatively influence the performance of the crypto companies' tokens.

Even though the results seem plausible and promising, it is important to note that the results for the third sub-question are statistically insignificant. Moreover, the regression results are likely to be biased. While there is no reason to suspect that a measurement error has been made, and even though the data has been checked for any obvious mistakes, Coinmarketcap, the source of the data, could have made a measurement error when collecting data for the public launch prices, as this data is likely to be collected manually from the whitepapers of the crypto companies.

Furthermore, while a couple of control variables and dummy variables to account for time fixed effects have been incorporated into the regression model, it cannot be guaranteed that all the confounding variables that are correlated with the main independent variables and affect the dependent variable are included in the regression model. Thus, there is likely to be some omitted variable bias.

The data used in this thesis spanned only one year, which is not a long time span. Moreover, the year 2021 was a breakout year for the whole cryptocurrency industry, 2021 was the year that cryptocurrency industry was put in the spotlight for investors, reporters, and entrepreneurs. Hence, it is not completely unrealistic that the returns for cryptocurrencies are so high in 2021. However, in the years prior to 2021, especially the formative years of the industry like the 2010s, it is likely that the returns were less significant since there was less attention on the industry. For future research, it is suggested that a longer period of time is used in order to fully understand the effects of launch platforms and blockchain networks on the performance of crypto companies' tokens.

Next to this, it is recommended that a more accurate proxy is used for both the independent variables. For launch platforms, the amount of webpage views was used as a proxy, as it measures how popular a launch platform is and thus how many potential investors there are. However, it can be argued that the popularity of a launch platform does not correspond with the amount of webpage views the platform gets. Perhaps a better proxy could, for example, be the amount of volume traded on the launch platform. This would be a bit more difficult as a token can also launch on their own website, thus eliminating the factor of volume traded. If the amount of volume traded would be used as a proxy, ICOs could not be used as they are the ones that launch usually on their own website.

Further, the proxy used for blockchain networks can also be argued to be dubious, as new consensus mechanisms can be developed and thus the rating scheme implemented can be outdated in the future. A better proxy could, for example, be the number of transactions on the blockchain network, or the amount of transaction fees paid on the blockchain network. These proxies would benefit from the phenomenon that most investors are likely to focus on profits first, and not the effect of energy consumption on the environment, or the electricity costs.

Even though this research can be improved, the results found in this thesis can be useful. For the theoretical implications, this research suggests that clearly launch platforms and blockchain networks can economically affect crypto companies. Thus, the theory studied in this thesis is capable of explaining and understanding the effects of launch platforms and blockchain networks on crypto companies. The results can be used as evidence by the scientific community that this area of research can be complemented and further improved.

For the practical implications of this thesis, investors can look at this research as evidence for investing in crypto companies' tokens that launch on more famous launch platforms and are built upon more economical blockchain networks. Entrepreneurs and creators can look at the results as evidence for making their company as economical as possible in terms of energy usage of the blockchain network used. Moreover, they can look at the results as evidence that even though launching on bigger and more famous platforms might be costlier, the returns on these platforms are also greater, and hence it might be worth launching on these types of launch platforms.

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Appendix

Figure 2 Graphical presentation of the price action of Bitcoin during 2021

Adapted source: Yahoo, 2022

```
import yfinance as yf
import pandas as pd

data = yf.download(['1ART-USD','1MIL-USD','2CRZ-USD','8PAY-USD','ACK-USD','ACM1-USD',
 … ,
 'ZAM-USD','ZENITH-USD','ZUKI-USD'], period='max', interval='1wk')

print(data)
data.to_csv('prices.csv')
```

Figure 3 The python code used to extract price data from Yahoo Finance ('…' to save space)

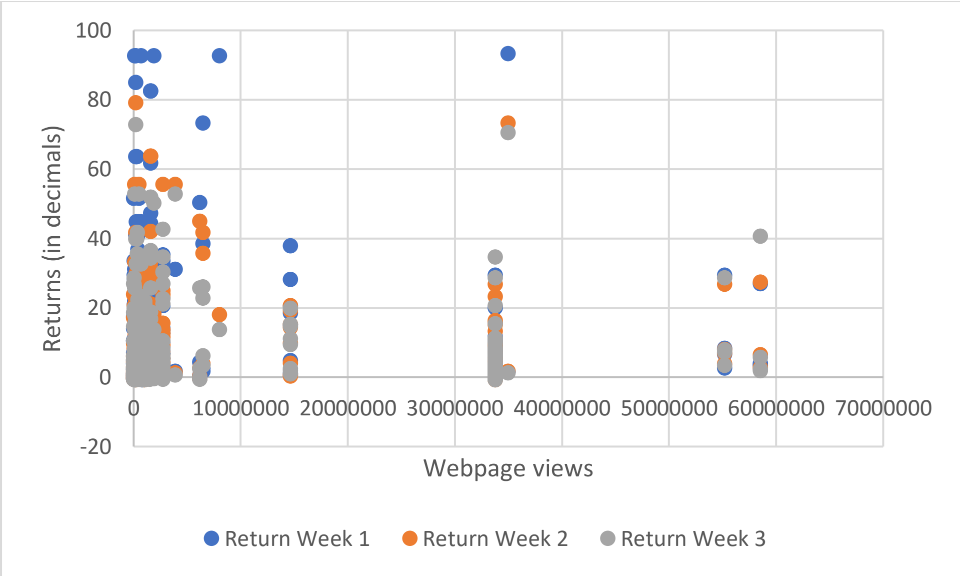

Figure 4 Scatterplot of the returns and webpage views for all three weeks, for the second assumption

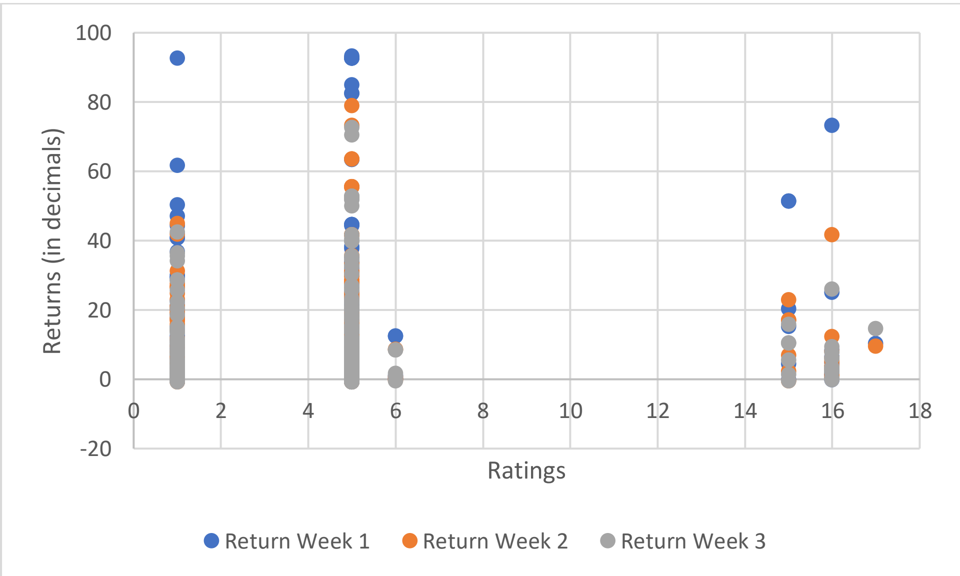

Figure 5 Scatterplot of the returns and ratings for all three weeks, for the second assumption

Table 4.1 The Pearson correlations between the explanatory variables, part one of the table

Variables	Bull Cycle	Raise Amount	February	March	April	May	June
Bull Cycle	-						
Raise amount	0.0748	-					
February	0.1163	0.2325	-				
March	0.3730	0.1950	-0.0290	-			
April	-0.0213	-0.0165	-0.0322	-0.1032	-		
May	-0.3640	-0.0630	-0.0423	-0.1358	-0.1509	-	
June	-0.2231	0.0519	-0.0259	-0.0832	-0.0925	-0.1216	-
July	-0.0598	-0.0282	-0.0231	-0.0742	-0.0824	-0.1084	-0.0664
August	0.2648	-0.0472	-0.0206	-0.0660	-0.0733	-0.0964	-0.0591
September	0.3340	-0.0194	-0.0259	-0.0832	-0.0925	-0.1216	-0.074
October	0.3992	-0.0495	-0.0310	-0.0994	-0.1105	-0.1453	-0.0891
November	-0.1592	-0.0247	-0.0427	-0.1369	-0.1521	-0.2000	-0.1226
December	-0.3156	-0.0443	-0.0367	-0.1177	-0.1308	-0.1720	-0.1054
Webpage views	0.0872	0.3511	0.3144	0.0843	-0.0336	-0.0360	-0.0368
Rating	-0.1049	-0.0485	0.0461	-0.1592	-0.0657	-0.0028	-0.0474

Table 4.2 The Pearson correlations between the explanatory variables, part two of the table

Variables	July	August	September	October	November	December	Webpage views	Rating
July	-							
August	-0.0527	-						
September	-0.0664	-0.0591	-					
October	-0.0794	-0.0706	-0.0891	-				
November	-0.1093	-0.0972	-0.1226	-0.1465	-			
December	-0.0940	-0.0836	-0.1054	-0.1260	-0.1734	-		
Webpage views	0.0203	-0.0246	0.0282	-0.0018	-0.0401	-0.0365	-	
Rating	0.0206	0.0807	-0.0700	0.0227	0.1031	0.0881	0.0839	-

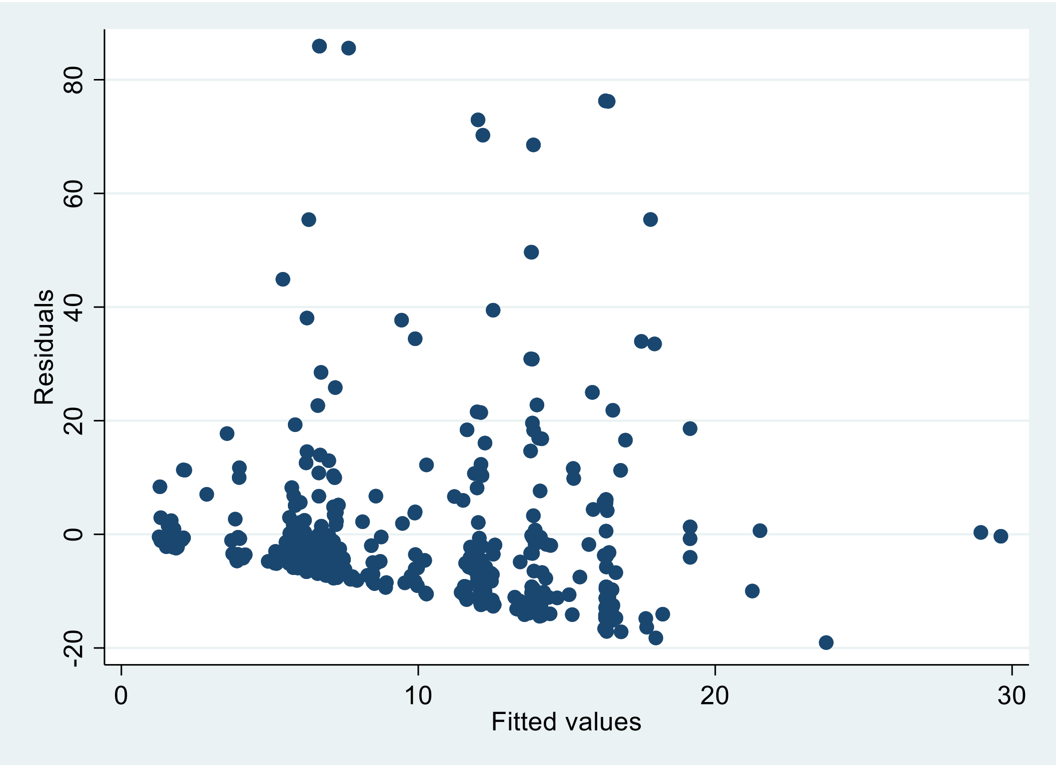

Figure 6 Scatterplot of the residuals and fitted values for model 1

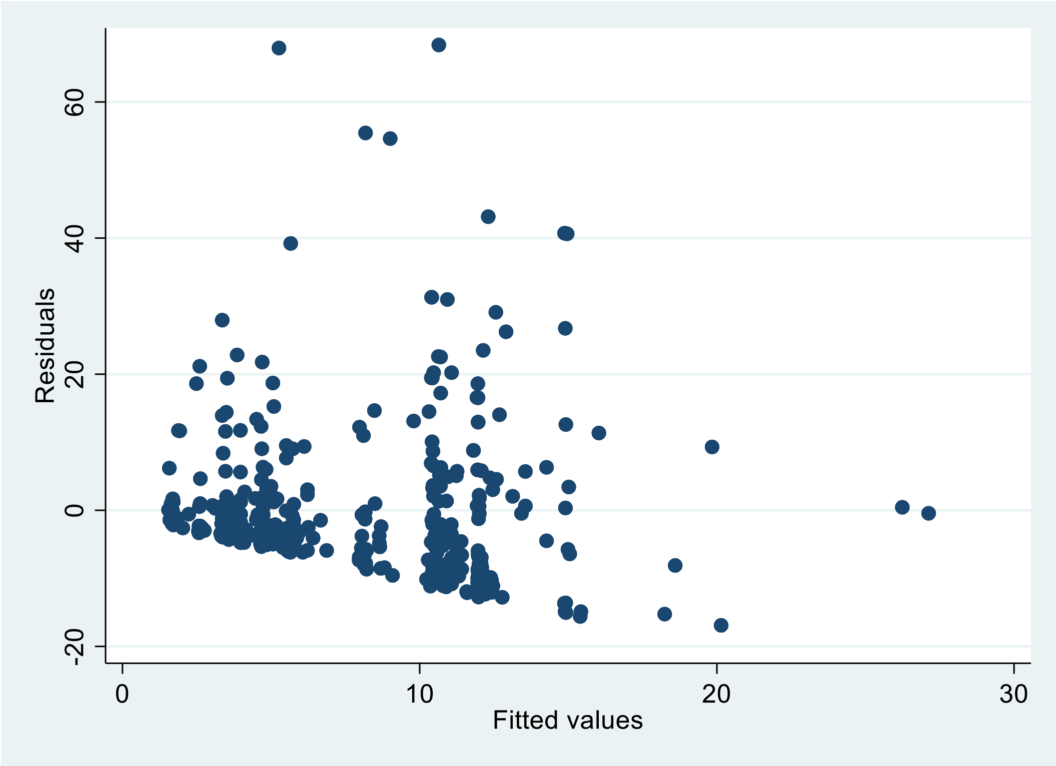

Figure 7 Scatterplot of the residuals and fitted values for model 2

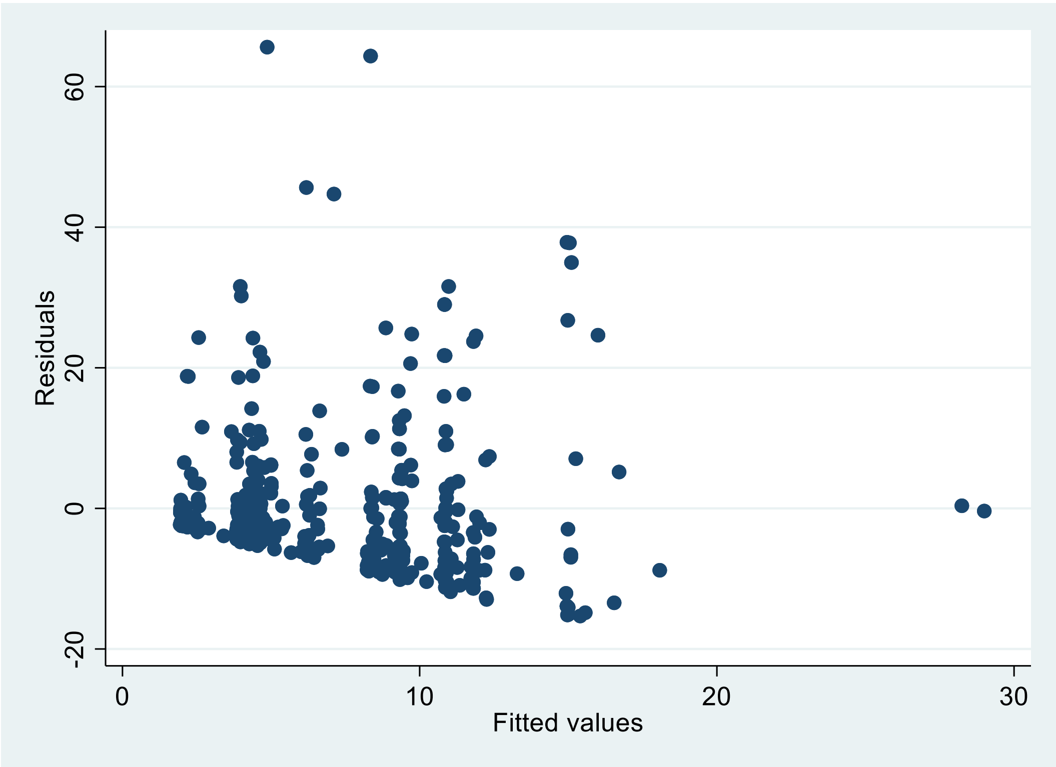

Figure 8 Scatterplot of the residuals and fitted values for model 3

Table 5 Results of the Breusch-Pagan tests for model 1, 2 and 3

	Model 1	**Model 2**	**Model 3**
X^2	42.86	62.86	61.57
p-value	0.0000	0.0000	0.0000

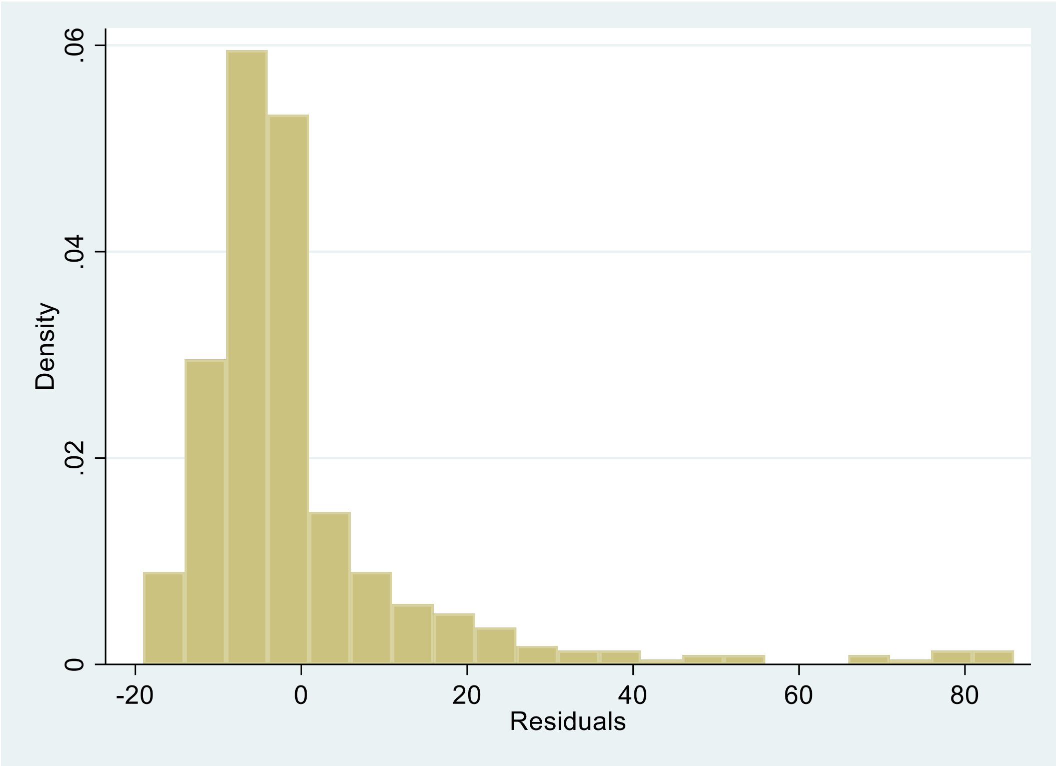

Figure 9 Histogram of the residuals for week 1 before log transformation

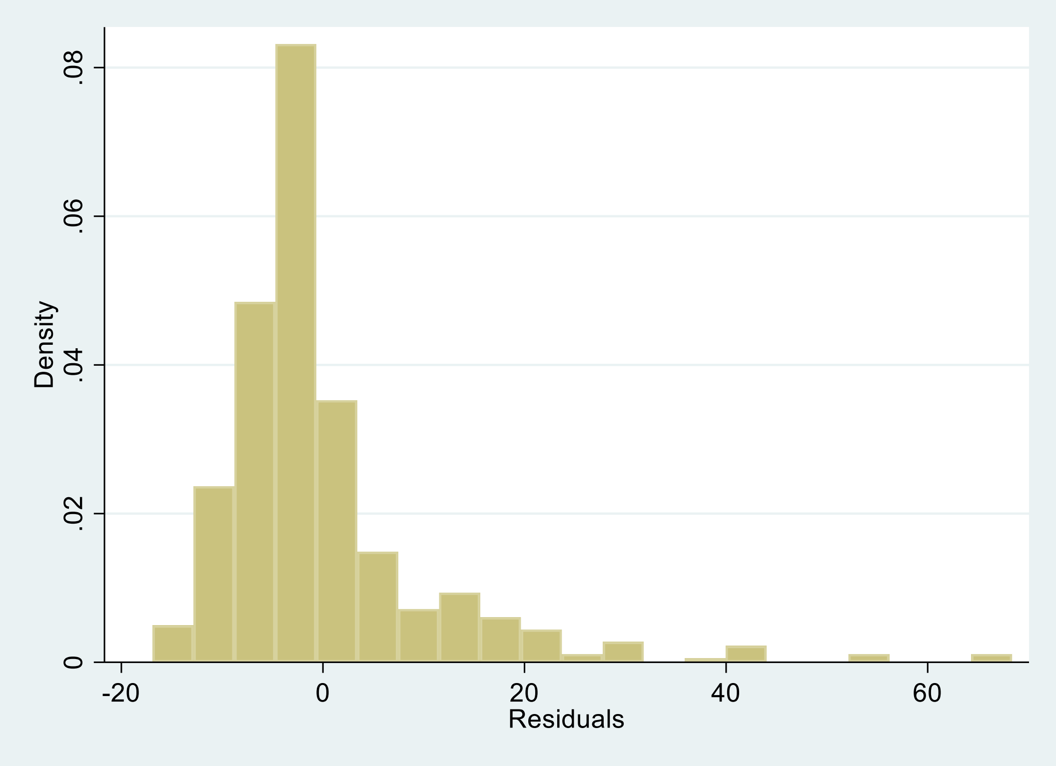

Figure 10 Histogram of the residuals for week 2 before log transformation

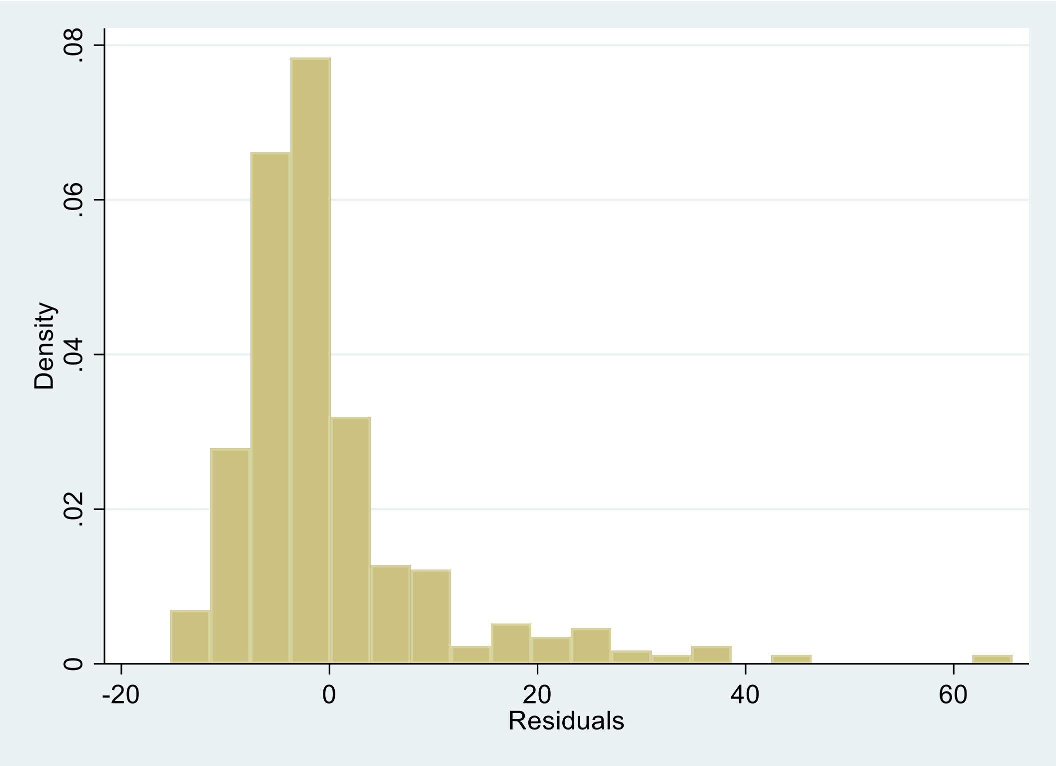

Figure 11 Histogram of the residuals for week 3 before log transformation

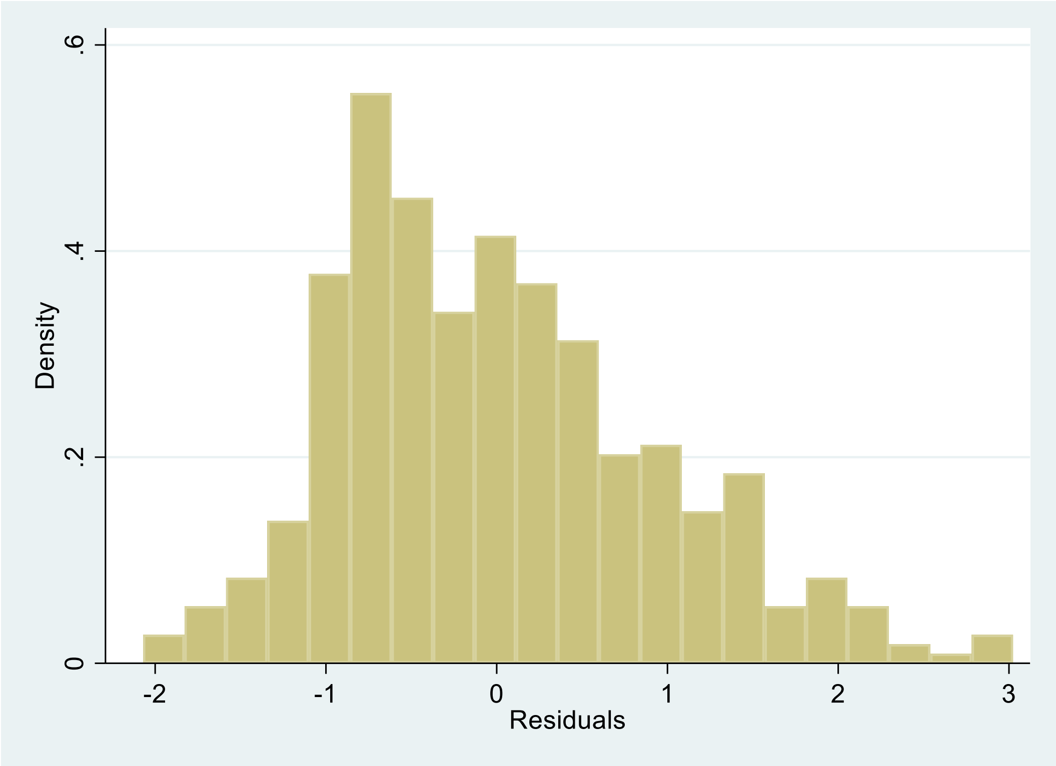

Figure 12 Histogram of the residuals for week 1 after the log transformation

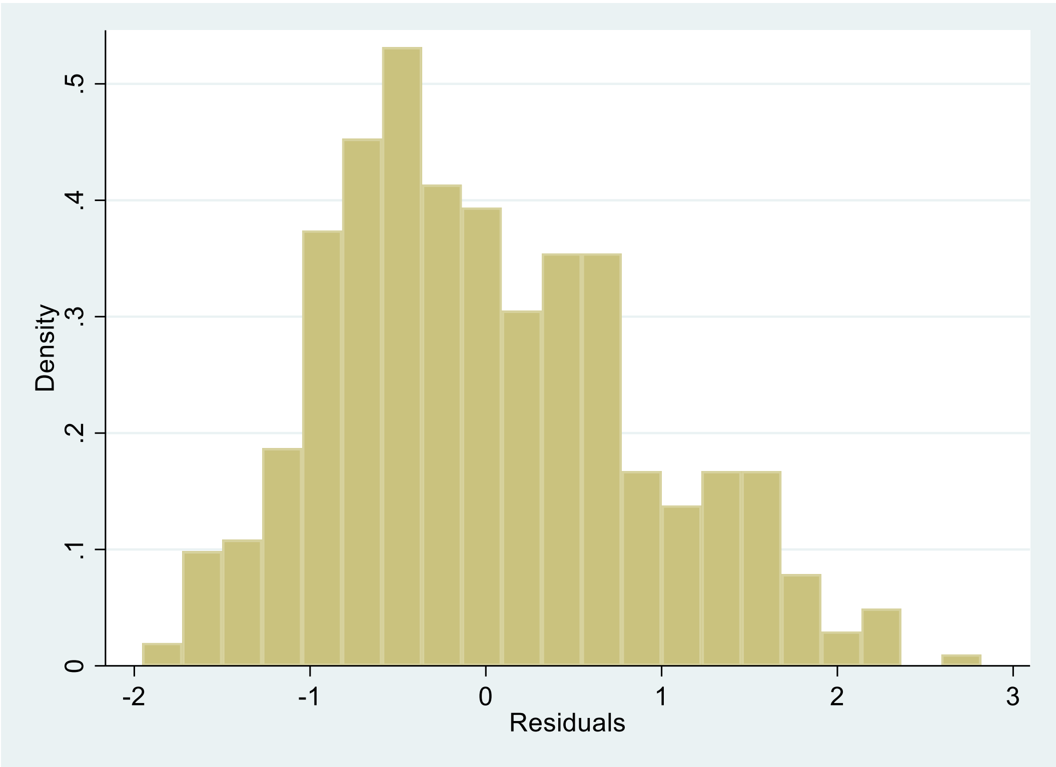

Figure 13 Histogram of the residuals for week 2 after the log transformation

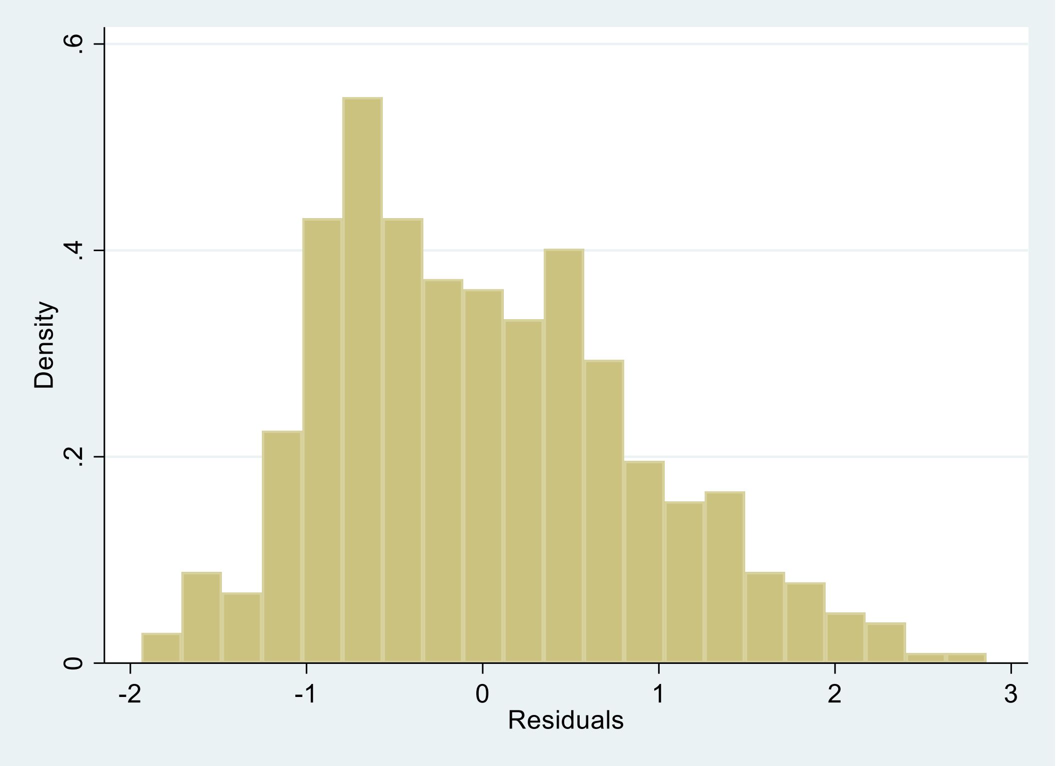

Figure 14 Histogram of the residuals for week 3 after the log transformation