Norwegian School of Economics
Bergen, Spring 2022

# Performance of Initial Coin Offerings, before and during COVID-19

*A comperative analysis of ICO performance before and during the COVID-19 pandemic*

**Surush Mohammad Hasanrash and Ashish Shrestha**
**Supervisor: Jøril Mæland**

Master thesis, Economics and Business Administration
Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

# Acknowledgements

This thesis is a part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH). Both authors major in Financial Economics (FIE). It has been a fascinating experience for us to explore and understand a trending asset type like ICOs. Foremost, we express our deepest gratitude to our supervisor, Associate Professor Jøril Mæland. She has been incredibly generous with her advise, suggestions and directions that helped us in conceptualizing and accomplishing this work. We are also grateful for both the prompt replies and the flexibility Jøril has allowed for during the entire process of writing this thesis.

We also want to express our gratitude to Professor Christian Fisch, University of Trier, and Professor Hugo Benedetti, Universidad de los Andes, for their quick response and guidance during the early stage of this thesis.

Finally, we want to express appreciation toward each other. It was a great teamwork and a fruitful learning experience during the entire period of this thesis.

Norwegian School of Economics

Bergen, May 2022



Surush Mohammad Hasanrash

Ashish Shrestha

Abstract

The research carried out in this thesis looks at the performance of Initial Coin Offerings (ICOs) in relation to the COVID-19 pandemic. ICOs listed before and after COVID-19 pandemic were collected and later compared to find significant differences. Collected ICO information were used to estimate a multivariate regression model to examine how different independent variables -funding predictors, raised capital and industry category-contribute to ICOs' initial return. Findings were then compared between ICOs listed before the pandemic with ICOs listed after the pandemic. We find that ICOs listed before the pandemic had significantly less initial return for investors compared to ICOs listed after the pandemic. Additionally, after comparing the long-term post ICO returns, our results indicate that the post ICO performance/long-term holding period returns were significantly more positive for ICOs listed and traded after pandemic.

***Keywords*** – ICO, Pandemic, Cryptocurrency

# Contents

# List of Figures

# List of Tables

# 1 Introduction

## 1.1 Background

After the financial crisis in 2008, the overall trust in capital markets was weakened (Martino et al., 2020). Trust in banks, governing bodies and financial institutions had been crippled. Many banks and other financial institutions were unsuccessful in delivering their obligations to the people and had been forced to be bailed out by the government at the expense of the taxpayers (Noogin, 2018).

One of the contributors to this global recession was the fractional reserve banking system, a banking system under which the banks have the liberty to 'spend' most of the deposits made by the banks' customers. For instance, if a bank has $10 billion in its assets, it is only obligated to keep $1 billion in reserves, or 10% of the total assets amount (Abel et al., 2017). This is a common system and rarely problematic as it would be highly abnormal for all the bank's customers to withdraw all their funds at the same time. However, in an extraordinary event, if numerous withdrawals were to be made, a bank can quickly be depleted of its mere 10% liquid reserves. The problem arises when the banks make poor investment decisions with the remaining 90% of the deposits, which was the case for the crisis. Bets on subprime mortgages, which was considered to be high risk assets, defaulted, leaving banks with significantly less valued assets (Noogin, 2018).

Not only did the financial crisis weaken the image of our modern financial system along with banks and similar institutions' financial stability, but it also created mistrust in fiat currencies[1] (Noogin, 2018).

Following the crisis, in 2009, a new innovative method of making payments rose through the ranks. This method would help diminish the interference of banks and other financial institutions when making an ordinary payment. This method would involve cryptocurrencies, most notably at the time was Bitcoin, which came to life during the same year. Although Bitcoin may not have been a direct response to the financial crisis (Acheson, 2021), it certainly sparked interest among individuals in the financial world.

[1] Fiat currency: Currency issued by a government, such as US Dollars ($) in the United States and NOK (Kr) in Norway.

According to Nasdaq Data Link (2022), the number of transactions made with Bitcoin in the year 2009, the year of its release, was 32,572. The following year, this annual figure rose to 185,921, which is a 570% increase. By the end of 2011, 2.12 million transactions were completed with the use of Bitcoin alone. This increase in activity and popularity of such a revolutionary technology had set the stage for a new innovative system. The blockchain technology, under which all the cryptocurrencies are based upon (including Bitcoin), has increased its area of usage which allows it to function in more and more business applications. Blockchain technology was such a strong breakthrough that it trumped the traditional Venture Capital firms (VC) in 2017 (Catalini and Gans, 2018; Boreiko and Sahdev, 2018). These start-ups and small and medium size enterprises (SMEs) that were operating under the blockchain technology would draw financial resources through the issuance of tokes or Initial Coin Offerings (ICOs) (Boreiko & Sahdev, 2018). According to a recent report published by ReportLinker (2022), the global market's estimated revenue for Blockchain technology was $2.5 billion in the year 2020 and is expected to reach $19.9 billion by 2026. With this significant and disruptive technology, a new wave of start-ups with blockchain applications would emerge.

The emergence of these blockchain backed start-ups required external funding for their business projects, the same way most start-ups would. Given these start-ups' highly technical nature they required extensive funding. They could either sell parts of their enterprise to external investors or borrow money from the local banks (Boreiko & Sahdev, 2018). We see that all these financing possibilities are tied to their geographical location, whether it be Venture firms, Angel investors, banks, or otherwise. This would implicate limitations for these enterprises, such as legal or legislative limitations among others (Boreiko & Sahdev, 2018). These financing options would become even less attractive for these enterprises since venture capital firms struggled to match the demand of so many newly formed start-ups that were looking for financing, which ultimately led them to look elsewhere (International Institute International Institute of Finance, 2018).

The financial crisis of 2007-2009 has undoubtedly affected the global financial market (Pereira da Silva, 2007). Similarly, the pandemic, being the most recent event, has had an enormous impact on a global scale. Not only has this event caused countless fatalities, but it has also affected the global economy (Saleemi, 2021). Though several financial commodities and assets have lost their value because of the pandemic, the crypto market has so far proven to have a positive market efficiency (Mnif et al., 2020; Saleemi, 2021). The activity of crypto assets, since the third quarter of 2019, has grown by over 2,300%. Similarly, the estimated global crypto-assets users have increased dramatically since 2020, whereas in 2021 there were estimated to be over 200 million users around the world (Feyen et al., 2022).

The pandemic clearly had a positive impact on the crypto market. It is currently experiencing a new wave of users, and the activity for crypto assets shows to be at an all-time high (Feyen et al., 2022). Previous research shows that a thriving crypto market also has a positive impact on Initial Coin Offerings (ICOs) (Masiak et al., 2020). ICOs, simply put, are novel mechanism of entrepreneurial finance that enables ventures, especially related to blockchain technology, to raise capital by selling tokens to a crowd of investors (Fisch and Momtaz, 2020).

Although there exists a good pool of literature that studied ICOs, there has been limited research conducted on the topic of the pandemic in relation to the ICOs. Now with enough data present, we can explore this field to find the impact the pandemic has had on ICOs. The financial significance of crypto market along with its increasing interest on ICOs as a crowdfunding tool makes this an attractive topic.

## 1.2 Research question

In this thesis, we examine the extent of the effects of the funding predictors, the raised capital, and the industry categorization on the ICOs' initial returns and their long-term returns. The literature review section, that follows, provides evidence on the effects the funding predictors- the ICO price, the ICO duration, the availability of whitepaper, and the operating platform of the venture- have on the ICOs' initial returns. However, due to limited data availability, there are no such established effects of these funding predictors on long-term ICO returns. Moreover, there are numerous articles on ICOs in terms of performance, but few mention the pandemic as a variable due to the recency of the pandemic. Thus, in this thesis, we intend to compare the effect of the funding predictors on the ICOs' initial returns and their long-term returns during two periods, pre-Covid and post-Covid. It is noteworthy to mention that the post-Covid period, in this thesis, refers to the period during which COVID-19 was considered as pandemic. Because the pandemic was announced in 2020, we have significant amount of data to work with. We believe comparing the ICOs that were listed and traded before the pandemic together with the ICOs that were listed and traded after the declaration of COVID-19 as a pandemic could show compelling differences. We hypothesize that the pandemic might have had an impact on the ICOs' performance. Hence, to explore the above discussion, we have ended up with the following research question:

"How do the funding predictors, the raised capital and the industry category affect the ICOs' initial and longer-term returns before and during the COVID-19 pandemic?"

To answer the above research question, the analysis of this thesis is divided into two parts. First, we explore the effect of the funding predictors, the raised capital, the industry category, and the crypto-market return on the ICO initial returns by establishing a multivariate regression model. Further, we introduce the pandemic dummy in our existing regression model to evaluate the effect of the pandemic on the initial ICO returns. Finally, we use all the independent variables from our model used to estimate the ICO initial returns to estimate the long-term returns, i.e., 180-days and 365-days holding period returns. This final model tends to explore the effects of these independent variables on the long-term returns of the ICO.

Drawing from the past studies (Benedetti & Kostovetsky, 2021; Hsieh & Oppermann, 2021), we hypothesize that the ICO price, the ICO duration, the raised capital, the availability of whitepaper, the platform used by the ventures, the industry categories and the crypto market returns may have an impact on the ICOs' initial returns. Although we could not find similar literature evidence for the long-term return periods, we hypothesize that these variables affect the long-term holding period returns of the ICOs, specifically 180-days and 365- days. Since the secondary investors, those investors who buy ICOs after they are listed on any exchanges, in the ICOs cannot buy these ICOs at the ICO price we have used the ICO listing price instead of the ICO price in our regression model for the long-term holding period returns. As the secondary investors draw expectations about the efficiency and the credibility of the ventures' ICO based on the time these ventures take to list their ICOs in the exchanges, we have replaced the ICO duration with the ICO listing duration for analyzing the effect of the ICO funding predictors on the long-term

ICO returns. On the contrary, the whitepaper availability, the platform of operation, and the crypto market movements affect both the initial ICO investors and the longer-term returns of the secondary investors in the same way; hence, we have not changed these variables when we estimated the longer-term ICO returns.

Recent studies (Dittmar & Wu, 2019; Jalan et al., 2021; and Katiampa et al., 2022) have highlighted the effects of the pandemic on the overall crypto market. Moreover, the study conducted by Hsieh and Oppermann (2021) found a significant effect of the crypto market returns on the ICO's initial returns. Thus, we expect that both the initial return and the longer-term returns of ICOs are affected by the period on which these ICO were listed and were available for trading. Specifically, we can hypothesize that the pandemic has some distinct effects on the ICOs' initial returns and their longer-term holding period returns.

## 1.3 Outline

The thesis consists of seven sections. The first section introduced the reader to the background in which this thesis was conceptualized. This section went on to present the research question which we have tried to address in this thesis. In section two, we build primary understanding of the cryptocurrencies and initial coin offerings followed by a brief highlight of cryptocurrency market during the pandemic. Section three, then, summarizes the key findings related to past ICOs studies and further elaborates on the performance of the cryptocurrency in relation to the pandemic. In section four, we present the data sources, the sample, and the time horizon as well as a justification of the selection criteria and the time horizon. Further, the data cleaning is explained before presenting the descriptive statistics. In section 5, we discuss the research design together with the explanation of the dependent and the independent variables used in the regression models. Section 6 presents the main analysis of the thesis. This section is divided into three major parts, the descriptive statistics, the explanation of regression models, and the discussion of the estimated regression models. Finally, section 7 presents the conclusion followed by the limitation and avenues for future research.

# 2 Market overview

## 2.1 Cryptocurrency

To grasp the idea of initial coin offerings (ICOs), we first need an adequate understanding of what a cryptocurrency is and the blockchain technology that operates beneath each cryptocurrency. Cryptocurrency is a virtual currency that acts as money and can be used to make payments without an intermediary. These cryptocurrencies are built on the blockchain technology, which is a distributed database that stores information electronically. The blockchain, which is an integral part of the cryptocurrency ecosystem, is responsible for maintaining a decentralized record of all transactions while also keeping this information secure (Benedetti and Kostovetsky, 2021). Fiat currencies require a central bank to guarantee their value, whereas cryptocurrencies are based on the blockchain which creates a "digital online distributed system of certification for payment transactions without any central authority" (Martino et al., 2019).

Before the inception of cryptocurrencies, there were no similar methods of payment. The closest resemblance to cryptocurrencies would be services such as Google Wallet and Apple pay, in the sense that they were virtual. These are, however, nothing more than a payment method and are based solely on fiat currencies. Cryptocurrencies are not supported by trust as fiat currencies do, but instead, they are supported by cryptographic proof (Martino et al., 2019), which is something entirely different. There were some earlier iterations of Bitcoin, such as DigiCash (1989), b-money (1998), e-gold (1996); though some of these were never implemented and others lacked success. It was Bitcoin's advancement that put blockchain and cryptocurrencies on the map (Kher et al., 2021).

In blockchain technology, Bitcoin was the first widespread application in effect, which was back in 2009. A year prior, Satoshi Nakamoto, published a nine-page whitepaper where he introduced Bitcoin as a virtual payment system. Due to the paper never being officially published in a journal, Nakamoto's identity remains a mystery. Nakamoto stated in his whitepaper that there were problems with the current electronic payment systems, that they had lack of security, and that Bitcoin would not have this issue. He further stated that there was no way of ensuring trustworthiness of the two entities at either end of the transaction using current electronic payment systems (Nakamoto, 2008). Just a few months after the paper's release, an open-source program that would later implement Bitcoin into a blockchain technology emerged (Martino et al., 2019). Shortly after, trading platforms for Bitcoin would surface and trading became possible. For one US dollar, you could buy 1309.03 Bitcoins, which was Bitcoin's first known trading rate. The first transaction for Bitcoin was in 2010 when it was used to purchase two pizzas for the price of 10,000 Bitcoins (Martino et al., 2019).

**Figure 2.1:** Log scale of a single BTC to US dollars (2010-2022)


Looking at the logarithmic graph in Figure 1, we observe a single piece of Bitcoin reaching one dollar in 2011, which was incredibly impressive at the time, especially considering 10,000 Bitcoins were used to purchase two pizzas. Just two years later, each Bitcoin was valued at USD 1000. And in November 2021, Bitcoin peaked at USD 68,990.

Following Bitcoin, countless other cryptocurrencies would hit the market along with other exchanges that enable users to exchange fiat currency for the desired cryptocurrency (Adhami et al, 2018). There are currently 18,465 digital currencies in existence, of which 10,363 still active as of March 2022 (Howarth, 2022). By comparison, there were only 50 cryptocurrencies by the end of 2013. Furthermore, as of March 2022, the market capitalization of all cryptocurrencies was $2 trillion with a previous peak of $2.9 trillion in November 2021. For the sake of comparison, the market capitalization was valued at $1 billion in 2013 and later $100 billion in 2017 (Coinmarketcap).

Following Bitcoin's major momentum, the enormous wave of cryptocurrencies would follow in Bitcoin's footsteps. Unfortunately, most of these virtual currencies would lack real value. They offered no utility or function to its users and were trying to clone Bitcoin with minimal changes (Martino et al., 2019). In fact, according to Bardinelli and Frumkin (2018) out of the top 100 cryptocurrencies, only 36 were identified to have a real working product[2].

## 2.2 Initial coin offerings

Ever since the emergence of cryptocurrencies and the popularity that came with them startups have been looking at ways of using this technology in their favor for securing funding (Martino et al., 2019). As mentioned previously, startups struggled to secure financing due to the increase in entrepreneurial activity due to the spike in the popularity of Bitcoin, which lead to an increase in emerging startups. This increase made it difficult for venture capital firms to match the demand, among other traditional financing means at the time (International Institute of Finance, 2018).

These startups introduced their cryptocurrency to take use of Initial Coin Offerings (ICOs) for fundraising. In the blockchain industry, the ICO had become the most popular method of seeking investments. Startups would use the ICO to issue cryptocurrencies in the form of tokens to their investors to raise capital. The tokens would be supported by an already existing blockchain protocol, and after launch, they can be sold internally to the investors (Wang et al. 2018). These tokens, depending on the startup's project, can later be used to interact with the final product or can be sold or traded. The tokens are highly volatile in nature and may increase or decrease in value. The team behind the project will also choose the selling price of the tokens before the ICO is initiated (Masiak et al., 2020).

ICO funding is like Initial Public Offering (IPO), but instead of stock, tokens are issued. Moreover, the tokens are purchased using cryptocurrency, often Bitcoin, Ethereum, or Ripple. The tokens can sometimes also be purchased using fiat currency, as you would

[2]Project's status, roadmap quality, release history, features, promise of delivery, availability, usage, and among other factors constitutes to a working product (Bardinelli & Frumkin, 2018).

with purchasing stocks (Masiak et al., 2020). During an IPO, investors who are issued stocks are given a share of the company, i.e., an ownership (Crain et al., 2021). By comparison, this is rarely the case in an ICO. Instead of a piece of the company, you get cryptocurrency in the form of tokens, which represents the company (Martino et al., 2019).

The ICO market is generally unregulated and each ICO tend to differ from other ICOs. But despite this, some processes are the same with every ICO. First, the actors contributing to the ICO process are always the same and often consist of four main actors. (1) The startup (often called the venture) seeks funding and is the organizer of the ICO campaign. (2) Investors, also known as the crowd-funders purchase tokens through an (3) intermediary, such as an exchange. And finally, the (4) contributors, which are often external entities or individuals who contribute to the ICO process. These contributors are often experts who add value to the ICO campaign as advisors, developers, and other roles classified roughly as 'external assisting staff' (Masiak et al., 2020).

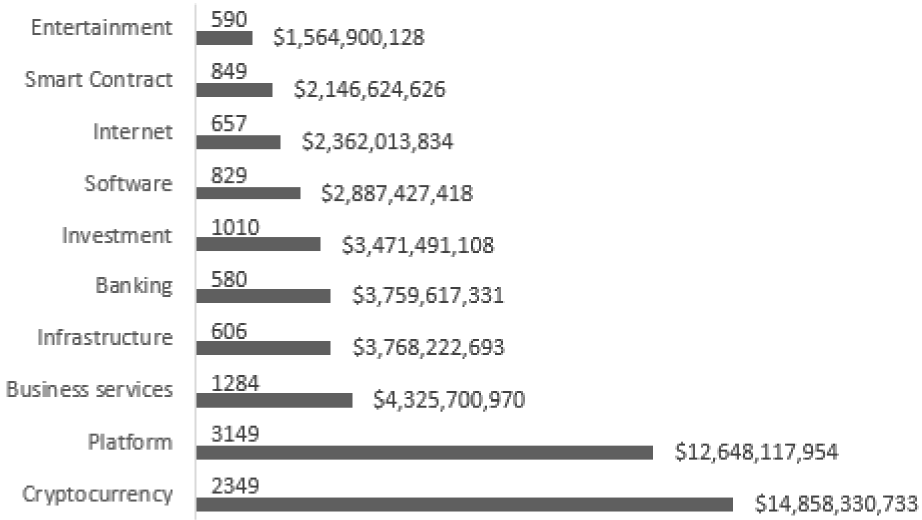
Additionally, the ICO process tends to also be similar. The process consists of three stages: Pre-ICO, Main ICO, and Post-ICO phase. First, the venture launches the ICO often by issuing a whitepaper, which is an informational document explaining the technology behind the product. The whitepaper will attempt to get the public's attention for reaching funding goals (Martino et al., 2019). During this phase, ventures may hire experts for increasing the chance of success of the ICO campaign and signal the quality of the technology to the audience (Maisak et al., 2020). These experts receive compensation often through the issuance of tokens and may receive other venture benefits (Fisch, 2019).

The main ICO phase consists mainly of promotion and use of schemes (Maisak et al., 2020). A typical scheme some ICO ventures use is selling a certain number of tokens for a discount, e.g., the first 10% of tokens may be sold for a 15% discount. This may push investors into buying tokens quickly before the discounted tokens are sold out (Fisch, 2019). Finally, the post-ICO phase consists of investors and other contributors seeking to exchange their tokens for fiat currency if the value of the tokens rises considerably (Maisak et al., 2020).

In Figure 2, ten of the most common ICOs are listed by industry. The diagram shows the total number of ICOs along with total market cap for each industry. Currently, there are

5728 ICOs and more than 29 different industries the blockchain based ventures operates in. As of May 2022, the highest valued single ICO (of sold tokens) is EOS, which is valued at \$4.2 billion (ICObench, 2022).

**Figure 2.2:** 10 most common ICOs by industry




Note: Number of ICOs and total market capitalization for each industry is illustrated above. Source: ICObench.com

## 2.3 COVID-19

The Covid-19 disease originated in Wuhan, China, and the first incident was reported in December 2019. Ever since the virus has spread globally impacting millions of lives. In less than 2 years, the outbreak had infected more than 200 million people worldwide and taken the lives of over 4.6 million individuals (Moore, 2021). Additionally, the outbreak had done extensive damage to the world's economy, and the damages are still experienced today. According to a report published in Statista, COVID-19 is responsible for a 4.5%[3] drop in economic growth, which accounts for \$2.96 trillion of lost economic output (Szmigiera, 2022).

The economic losses of the pandemic were more imminent in China, especially during the pandemic's earlier stages. International airlines halted, shipping ports experienced cutbacks, business operations overseas declined. Hyundai (a major Korean car manufacturer) halted its car manufacturing operations due to production taking place in China. The outbreak was so impactful, that the Chinese stock market dropped by 8% in

[3]Of global GDP (Szmigiera, 2022)

the following months, a drop that had not been experienced in the last four years (Jana & Das, 2020).

The financial market is the most important market in the global economy. It provides growth to an economy, expands financial infrastructure, and enhances domestic and foreign trade (Adrian, 2021). The unprecedented challenges posed by the pandemic have put the financial market on a path of economic decline. Understanding the relationship between the pandemic and the impact it has on various markets can help the global economy's ability to cope with similar external events in the future.

Though several financial commodities and assets have lost their value because of the pandemic, the crypto market has so far proven to have a positive market efficiency (Mnif et al., 2020; Saleemi, 2021). The activity of crypto assets, since the third quarter of 2019, has grown by over 2,300%. Similarly, the estimated global crypto-assets users have increased dramatically since 2020, whereas in 2021 there were estimated to be over 200 million users around the world (Feyen et al., 2022). The pandemic clearly had a positive impact on the crypto market. It is currently experiencing a new wave of users, and the activity for crypto assets shows to be at all-time high (Feyen et al., 2022).

# 3 Literature review

This section consists of related past research on ICOs along with how this thesis fits into the existing literature. We summarize the key findings of ICO studies which we later compare with our findings. We then highlight findings from studies conducted on the topic of the crypto market in relation to the COVID-19 crisis. To the author's knowledge, there are no existing studies that cover the topic, specifically, related to the ICOs returns and the pandemic. Finally, at the end of this section, we discuss how our thesis contributes to the existing literature.

## 3.1 ICO returns

Most of the literature on cryptocurrency has focused primarily on Bitcoins. One of the first known studies about ICOs, in the financial literature, was conducted by Adhami et al. (2018). The paper analyzed the variables, so-called characteristics of ICOs, that could determine the success of an ICO. According to the authors, the ICOs that managed to reach their minimum funding goal were considered successful ICOs. Similarly, they found that ICOs that disclosed the underlying codes and those ICOs that conducted pre-sales had a significant effect on ICOs' success.

One of the first studies on the ICO returns was done by Benedetti and Kostovetsky (2021). This study was conducted in 2018 using the information of ICOs completed before April 2018. Benedetti and Kostovetsky (2021) found significant under-pricing in ICOs implying that tokens that are sold through initial coin offering are priced at a significant discount to their market prices. They found a significant relationship between log ICO price and log ICO initial returns. They also calculated token's return after the asset is listed on an exchange. The findings were that prices continued to drift higher, witch generated higher returns for secondary investors within 30 days (Benedetti & Kostovetsky, 2021).

Similarly, Hsieh and Oppermann (2021) examined ICO initial returns and their determinants. They found that a pre-sale and a lengthy white paper had negative effects on the initial returns, while having a shorter duration and running on an independent blockchain had positive impact. They identified strong influence on the cryptocurrency market on ICO initial returns. ICOs that were listed during the bubble (bear market) period has resulted in higher (lower) initial returns. Additionally, they found that the industry to which the ICO belongs in is another significant factor in determining the initial returns.

From previous studies on the ICOs initial returns, it is implied that the ICO initial returns are effected by the ICO prices, ICO duration, availability of whitepaper and platform used by ventures which we are jointly calling as funding predictors. Moreover, past literature also suggests some effect of the industry categorization on the ICO initial returns. We use these evidences from past studies to evaluate our findings.

## 3.2 COVID-19 and cryptocurrency performance

In the following paragraphs under this section, we review studies conducted on cryptocurrencies or the cryptocurrency market in relation to the COIVD-19 pandemic. We review these studies to understand whether the pandemic has had an impact on cryptocurrencies, and the type of impact.

Previous literature shows that although the pandemic may have had an extensive negative effect on the financial market, the cryptocurrency market is affected positively. According to Huang (2022), prices of cryptocurrencies are positively affected in the short run because of the pandemic. Huang (2022) suggests investors to hedge risks associated with the pandemic by utilizing the performance of the cryptocurrency market. Similarly, a paper written by Mnif et al. (2020) studied five major cryptocurrencies during the pandemic and found that all of them became more efficient post-pandemic. These studies show a clear link between the pandemic and its positive impact on the cryptocurrency market. It is however important to note that the study conducted by Mnif et al (2020) does not portray a clear view, due to their time frame in data going up until May 2020. Especially considering COVID-19 was declared a pandemic in March 2020. Though in contrast, Huang's (2022) paper is more significant with an end date in time frame going up until November 2021 which we argue to be more telling.

In a recent paper written by Katiampa et al. (2022) the same topic was explored. They examined Bitcoin and thirty-one other crypto assets between January 2019 to December 2020. They found that altcoins[4] became significantly more popular during the

[4]Altcoins are all cryptocurrency except for Bitcoin

COVID-19 crisis. They argue that this rapid spike in popularity could be explained by increased institutional investors' interest in the cryptocurrencies, which could mainly be reasoned by the lack of performance observed in traditional investment markets because of the crisis. Additionally, Katiampa et al. (2022) point out that altcoins that offer functionality and business application were more attractive to these investors rather than pure cryptocurrencies.

Jalan et al. (2021) took a different approach in their paper. They analyzed five stable cryptocurrencies instead, more specifically gold-backed coins. These stable coins tend to be less volatile than traditional cryptocurrencies because they are backed by gold. Jalan et al. (2021) compared these stablecoins with gold, Bitcoin, and Tether during the COVID-19 pandemic and found that the stablecoins' volatility was comparable to that of Bitcoin. They also concluded that gold-backed cryptocurrency did not have safe-haven properties against the physical counterpart, gold. This may suggest that under external and unprecedented uncertainties, cryptocurrencies backed by assets such as gold are affected negatively by the pandemic whereas regular cryptocurrencies are affected positively.

In our next review, we examine Dittmar and Wu's (2019) paper that compiled a dataset consisting of ICOs ranging from 2014 to 2019. They discovered several remarkable findings, including ICO performance in relation to the 2018 cryptocurrency crash. ICOs performed remarkably well, both in the long term and after the cryptocurrency market crash. They found out that ICO cryptocurrencies significantly outperformed non-ICO cryptocurrencies (Dittmar & Wu, 2019). This may indicate ICO cryptocurrencies to act more independently than non-ICOs and show better market performance during the cryptocurrency market crash in 2018, which was also an unprecedented uncertainty.

The abovementioned papers are a fraction of the total relevant papers we could have drawn in this literature section. However, the literature currently available looks specifically at the cryptocurrency market. ICOs in relation to the crisis have not yet been explored. Thus, this thesis contributes to the existing literature by exploring the relationship between ICO funding predictors, ICOs returns, and the COVID-19 crisis. We argue that the effect of these variables has varied on the ICOs' initial returns and the ICOs' long-term returns depending upon whether they were listed and traded in the pre-Covid or the post-Covid period. Therefore, our contribution to the literature is to investigate whether the funding predictors, the industry categorization, and the crypto market return impact the ICOs' initial returns and their long-term returns differently during the pre-Covid and the post-Covid period.

# 4 Data

## 4.1 Data sources

A universal database for ICOs does not (yet) exist to the extent of our knowledge. However, we did find a work-in-progress database named Token Offerings Research Database (TORD) maintained by Paul P. Momtaz (Momtaz, 2021). TORD contains information about more than 6,400 ICOs that ended until October 2021. The data available in TORD is relatively comprehensive to identify information regarding ICO characteristics such as: start date, end date, website, whitepaper, listing, country of origin, and ICO price. As our study focuses on the return analysis of pre-Covid and post-Covid ICOs, we found the information available in this database of limited use. Hence, we opted to collect the data manually.

Many ICO aggregator websites are available online that provide different information about ICOs. Some of those aggregator websites are, for instance, icodata.io, icobench.com and ICOdrops.com. These websites compile the ICO characteristics information such as start date, end date, ICO price, token offered, total token supply, platform, raised capital, website, whitepaper, and industry category. Thus, these aggregator websites were used as the main source of ICO characteristics information.

Financial data such as raised capital, listing date, listing prices, post ICO prices at different times were collected from Coinmarketcap (Coinmarketcap, 2022). Coinmarketcap (CMC) functions as a universal listing platform that includes all tokens and coins trading on several exchanges. CMC is widely considered the best available data source for cryptocurrency prices and volume (Benedetti & Kostovetsky, 2021). CMC requires organizations to submit a form to list their currencies; so, there is occasionally a small lag between the exchange listing date and the date when prices start appearing on a website (Benedetti & Kostovetsky, 2021). Price data of the ICOs used for the thesis work were collected from CMC in US dollars.

## 4.2 Data sampling and time horizon

World Health Organization (WHO) declared Covid-19 as a pandemic on March 11, 2020 (World Health Organization, 2020). We have used this cut-off date to collect the sample of data to perform return analysis on ICOs. At first, we used convenience sampling to select the aggregator website for the source of data. All aggregator websites have their ways of reporting ICOs' information. We scanned through several aggregator websites and found that ICOdrops.com has ICOs' information arranged in a manner that was most relevant for us. Benedetti and Kostovetsky (2021), ranked ICOdrops.com as the second-best accurate source for ICO characteristics data including ICO prices. Thus, we decided to use ICOdrops.com as our main source of ICO characteristics data.

Furthermore, we dumped all the ICO data available on ICOdrops.com in MS excel. These data set included data from 2014 to 2022. As our focus was to perform return analysis on the ICOs, it made no point to incorporate all those ICOs which were ongoing. Thus, we filtered out the ongoing ICOs. Moreover, for the return analysis we needed ICOs that had some sort of price information. Therefore, we further filtered out ICOs that were not listed before April 1, 2022. By deciding on the cut-off date of April 1, 2022, we implicitly had 24 months period after Covid was declared as a pandemic. Hence, we had 24 months' time horizon for post-Covid ICO data. Moreover, for uniformity of time horizon, we decided to include ICOs that ended after January 1, 2018, to April 1, 2022, giving us a period of 51 months, 27 months before Covid and 24 months after Covid.

## 4.3 Data collection process

After we decided the data source, sample, and time horizon the main task was to collect all possible information required for the analysis. As mentioned earlier, ICOdrops.com and CMC were the two main sources of ICO characteristics and market data, respectively.

We collected ICO characteristics information from ICOdrops.com website. Our ICO characteristics information includes ICO start date, ICO end date, ICO price, interest, category, platform type and availability of whitepaper. In addition, we identified ticker symbol, token/platform name and website URL as three identifiers. Based on these identifiers, we matched the ICOs that were available in both ICOdrops.com and CMC. When we merged the datasets, we were left with 1,103 ICOs, including 357 ICOs which were completed between January 1, 2018, to March 11, 2020, and 746 ICOs which were completed between March 12, 2020, to March 30, 2022.

Based on the identifiers, we first collected the listing date of these ICOs from CMC.

Listing date, here, implies to the first date on which the ICO was listed in any of the exchanges that were aggregated by CMC. We cross verified the listing of an ICO based on the market summary statistics given on ICOdrops.com. ICOdrops.com have a section named Market & Returns which highlights the current market performance of an ICO. We matched the current price information in the Market & Returns section to the current trading price in CMC, it can also be thought of as another identifier.

After manually recording the listing date, using MS excel, we identified the dates that represented 1-day, 7-days, 14-days, 30-days, 90-days, 180-days, and 365-days after listing. We then manually collected the prices of these ICOs for all those dates. We primarily focused on the US dollar prices on these different dates.

## 4.4 Data cleaning

Data cleaning was important to determine the final set of usable data. In the study conducted by Benedetti and Kostovetsky (2021), they started with a pool of 2,390 observations but their analysis was conducted on 627 observations which represent approximately only 27usable data. A similar reduction in usable data was noted during our data cleaning process.

We started our data cleaning by filtering out any ICOs that did not have a start or end date. Then, we excluded any ICOs that did not have listing dates. Finally, we removed ICOs without ICO price. After these data cleaning steps, we arrived at observations with some price information, if not all. We could have further cleaned the data for time horizon but we opted to keep those at this stage as we decided to construct different data subsets to perform the return analysis in terms of price information available at different dates.

Most of the studies on ICOs conducted in the past are based on the information available on several of these ICO aggregator websites. Authors of those studies are vocal about the possible survivorship bias in those datasets of ICOs (Fisch, 2019; Benedetti & Kostovetsky, 2021) and same survivorship bias also applies to our dataset.

# 5 Methodology

## 5.1 Research design

The analysis of this thesis is mainly twofold. First, we intend to study the underpricing (initial returns) of these ICOs when they are listed on an exchange, CMC. We further explore the effect of funding predictors on the initial returns of these ICOs. Adhami et al. (2018) conducted a study where they analysed different variables that might determine the success of an ICO. In their study, an ICO was considered successful if the minimum funding goal was achieved. We have used some of those variables and called them as funding predictors. Specifically, we have used ICO characteristics such as ICO price, ICO duration, availability of whitepaper and Ethereum platform as funding predictors. Moreover, previous studies on ICO initial returns conducted by Benedetti and Kostovetsky (2021) and Hsieh and Oppermann (2021) found a significant relationship between capital raised and ICOs' initial returns. Thus, we have also included logged raised capital as one of the independent variables.

Secondly, this thesis also intends to study the effects of the same funding predictors on the return of the secondary investors, investors who invested in these ICOs after they were listed. For these secondary investors, we first calculated the holding period return for different holding periods ranging from short-term (1-day) to longer-term (365-days) returns. Then, we established a multivariate regression model to examine the effect of the funding predictors on the 180-days and 365-days holding period returns of the secondary investors. Finally, we introduced pandemic dummy, which is our primary interest variable, as a control variable, to analyze whether listing before Covid and after Covid influences both the ICOs' initial returns and returns for secondary investors.

We have collected data on 1,103 ICOs including both pre-Covid and post-Covid listings. Using ICO price and secondary price data after listing, we conducted a quantitative study to enrich our analysis. Thus, the analysis in this thesis is based on numerical comparison and statistical inference. For analyzing the returns of secondary investors, we have collected historical prices from the respective first day of listing until 365 days for both pre-Covid and post-Covid subsets. Since we were interested in estimating effects on cumulative returns across ICOs, not the daily returns, we treat these time-series as cross-sectional data, for 1-day, 7-days, 14-days, 30-days, 90-days, 180-days and 365-days snapshots.

## 5.2 Dependent variables

### Returns

Our first set of analysis examines the return to token buyers (initial investors) who invested through ICOs. To determine the initial returns of the ICOs/tokens, we follow the basic approach of Initial Public Offering (IPO) initial returns (Ritter & Welch, 2002) which was also used by Hsieh and Oppermann (2021) and Benedetti and Kostovetsky (2021). We calculated the initial returns as the logged difference between the first available (opening) price on CMC and the offer price during the ICO as used in Benedetti and Kostovetsky (2021). While, Hsieh and Oppermann (2021) used the closing price on the first day of listing for initial return calculation, we have used the first day opening price because we are also interested to examine the 1-day holding period return of secondary investors who would purchase the ICO when they are listed (at opening price) and sell it at the end of the day (at closing price). Moreover, we have used logged price to get a linear relationship between observations and that can be used without bias in the Ordinary Least Square (OLS) regression. The price is denominated in USD and the first day return is calculated as:

$$Initial\ Return = log(P_{first}) - log(P_{ICO}) = log(P_{first}/P_{ICO}) \tag{5.1}$$

where $P_{first}$ is the opening price at the first trading/listing day and $P_{ICO}$ is the offered price during ICO.

Similarly, holding period returns of the secondary investors were calculated using the above equality after making adjustments to different holding periods. The price for each holding period is denominated in USD and the different holding period returns are calculated as:

$$
\begin{aligned}
1Day\ Return &= log(P_{1day\,close}/P_{1day\,open}) \\
7Days\ Return &= log(P_{7day\,close}/P_{7day\,open}) \\
14Days\ Return &= log(P_{14day\,close}/P_{14day\,open}) \\
30Days\ Return &= log(P_{30day\,close}/P_{30day\,open}) \\
90Days\ Return &= log(P_{90day\,close}/P_{90day\,open}) \\
180Days\ Return &= log(P_{180day\,close}/P_{180day\,open}) \\
365Days\ Return &= log(P_{365day\,close}/P_{365day\,open})
\end{aligned} \tag{5.2}
$$

## 5.3 Independent variables

Furthermore, we intend to understand different aspects of the influence on the initial returns of ICOs; hence, we examine a variety of variables. An ICO can be viewed as a form of fund raising, some characteristics are like those of IPOs and crowdfunding (Hsieh & Oppermann, 2021). We examine the influence of a wide variety of variables resembling ICO characteristics, cryptocurrency market, industry segment and time. In the following section, we briefly explain the variables that were considered for the analysis.

### 5.3.1 ICO characteristics

The ICO characteristics can be divided into fundamental information and signals of quality (Hsieh & Oppermann, 2021). Fundamental information about the ICO implies information related to ICO duration, raised capital, information on pre-sale, bonus, token supply, hard capital, country of origin etc. (Fisch, 2019). However, we have only considered ICO price, ICO duration and raised capital as variables that represent fundamental ICO characteristics for the analysis.

Whitepaper and platform standard signal the competence of the technical team and establishes trust on the ventures. Ethereum's Ethereum Request for Comment (ERC20) is a blockchain technology that ICO ventures can build on. Thus, ventures built on the ERC20 platform signal trust for the investors. Therefore, we have used whitepaper and platform standard as signals of quality that might affect the initial returns of ICOs.

### ICO price

Hsieh and Oppermann (2021) found that ICO investors suffered from nominal price illusion which caused higher market demand for tokens with low nominal prices and thus, higher returns relative to the ICO price. Nominal price illusion in the tendency of stock investors to overestimate the room to grow from low priced stocks relative to high priced stocks (Birru & Baolian, 2016). Thus, to examine if such nominal price illusion still existed we have incorporated natural log of the nominal ICO offer price as one of the independent variables. As price information is fundamental and disclosed to the investors prior to their invesment decision we have incorporated it in the ICO characteristics.

### Raised capital

Raised capital is another independent variable in our estimated model. It represents the amount raised by a venture throughout the ICO duration. Howell, Miessner, and Yermack (2020) highlighted that the funding amount received by the ICO provides an indication of public interest in the venture, thereby signaling popularity and liquidity once listed. Such liquidity always attracts investors for speculative trading. ICO investors are speculative traders (Benedetti & Kostovetsky, 2021); thus, we have incorporated natural log of raised capital as another independent variable.

### Whitepaper (dummy)

Ventures usually, but not always, publish whitepaper where they describe their project concept, development plan and goal. It represents the technological capability of the venture's team to bring the project to operation. Fisch (2019) in his study found that the availability of whitepaper significantly influenced the success of ICO and the amount raised. Moreover, the length of whitepaper had a significant negative effect on ICO returns indicating that investors value a precisely formulated whitepaper (Hsieh & Oppermann, 2021). We neither have access to the length of whitepaper nor have the expertise to evaluate the content of whitepaper; thus, we considered only the availability of a whitepaper as one possible variable affecting the ICO returns.

### Ethereum (dummy)

Ethereum standard (ERC20) is the most common token standard (as of 2020) (Fisch & Momtaz, 2020). Its advantages include greater interoperability with other tokens, a more advanced infrastructure, and access to network externalities (Fisch, 2019). Fisch (2019) found that ventures that build on ERC20/Ethereum achieved higher valuation than those building on their own platform or drawing on different standards. Thus, we have included this dummy to see the effect of platform on ICOs' initial returns.

### 5.3.2 Industry category

Hsieh and Oppermann (2021) found that ICOs related to high-tech services and platform products have significantly higher returns while ventures related to finance and entertainment sectors have no significant influence on initial returns. This is relevant as ICOs are implemented with a goal to raise funds to develop an online platform focusing on some specific industry. Thus, to examine the effect of industry on the initial return of an ICO, we have incorporated an industry category as a dummy variable. We have grouped our observations into six industry groups, namely blockchain technology services (BTS), fintech, entertainment and media (ETM), marketplace (MP), high-tech services (HTS) and others. This categorization was mainly influenced by ICOdrops.com. Moreover, we have further rearranged the grouping based on the most recurring industries in the data set.

**Blockchain technology services (BTS)**

BTS includes all the companies which provide some specific services built on or related to blockchain. This includes blockchain platform providers, blockchain services, smart contracts, platforms and protocol services. Since, it is a dummy variable BTS holds the value of 1 if the venture was affiliated with these services, and 0 if it does not.

**Fintech**

Fintech includes all those companies that provide some services in the finance sector. Specifically, it includes ventures providing services in banking, business, cards, crowdfunding, currency, exchange, insurance and payments. As a dummy variable Fintech takes the value of 1 if the venture operates in the finance sector, as mentioned, and 0 if it does not.

**Entertainment and media (ETM)**

Ventures that provide services in education, social network, video streaming and gaming were included in this category. Similar to BTS and Fintech, it takes the value of 1 if the venture operates in entertainment and 0 if it does not.

**High-tech service (HTS)**

This dummy includes those ventures that provide services in artificial intelligence, cloud services, DAPP, data services, hybrid intelligence, Internet of Things (IOT), platform, protocol and security services. It takes the value of 1 if ventures fall in one of these category and 0 if it does not.

**Marketplace (MP)**

Ventures such as advertising, e-commerce, marketplace, marketing and trading fall under this group and take the value of 1 and 0 if it does not.

**Others**

All other ventures which had a smaller set of observations and did not fall in the above categorization were included in this category.

### 5.3.3 Control variables

**Bitcoin and Ethereum returns**

Like in IPO markets where general market can have a strong impact on intial returns, ICOs' initial return are affected by the crypto currency markets as well. Since Bitcoin is the longest existing cryptocurrency and has the largest market capitalization, it can be seen as a market benchmark for measuring returns (Ciaian & Rajcaniova, 2018). Moreover, as many ICOs are operated through smart contracts running over Ethereum platform, Ethereum too is an important cryptocurrency market indicator. Thus, we found it reasonable to include Bitcoin and Ethereum return as a control variable for the estimated model. We have maintained similar consistency while calculating the return of Bitcoin and Ethereum. Specifically, we have used log returns based on the closing price of Bitcoin and Ethereum on the closing date of the ICO and the ICO's first listing date when we calculated the initial returns. Likewise, we have calculated the holding period returns of Bitcoin and Ethereum for different holding periods using the closing prices of Bitcoin and Ethereum at the end date of each holding period and ICO's first listing date.

**Pandemic**

The cryptocurrency market is often asserted as a speculative market with ICO participants investing not based on the venture's proposed innovation/technology itself but because of strong herd behavior and fear of missing out (Zetzsche et al., 2019). To examine whether similar instances also hold during the pandemic, we separate the sample into two periods, namely, pre-Covid and post-Covid. A pre-Covid sample includes ICOs that ended between January 1, 2018, to March 11, 2020, while a post-Covid sample includes ICOs that ended on March 12, 2020, till March 31, 2022. Hence, the pandemic is a key control variable in this analysis both for the initial returns and the holding period returns.

## 5.4 The regression model

In our first analysis, we intend to examine the effect of each variable on the initial return of a token. Initial return is a ratio scaled variable. Hence, we use an OLS regression model (Moutinho & Hutcheson, 2011). More specifically, we formulate a multi-variate regression model.

Multiple regression models allow for inference through statistical tests under certain assumptions, also known as Gauss-Markov assumption (Wooldridge, 2020). These assumptions are that the model is linear in the parameter ($\beta$), the model has a random sample of n observations, none of the independent variables of the model are constant and there are no exact linear relationships among the independent variables, and zero conditional mean assumption.

Thus, to examine the initial returns of ICOs, the following model is estimated:

$$\begin{gathered} IR_i = \alpha + \beta_1 log(ICO\ Price_i) + \beta_2 log(RC_i) + \beta_3 ICO - Duration_i + \\ \beta_4 Whitepaper_i + \beta_5 ETH_i + \beta_6 BCR_i + \beta_7 ER_i + \beta_8 BTS_i + \beta_9 ETM_i + \\ \beta_{10} Fintech_i + \beta_{11} MP_i + \beta_{12} HTS_i + \beta_{13} Others_i + \beta_{14} Pandemic_i + \epsilon_i \end{gathered} \tag{5.3}$$

The majority of the independent variables in model 3 are similar to the model established for holding period returns (model 4). Thus, we define the independent variables of both the model 5.3 and the model 5.4 in Table 5.1.

Brief definition of these variables is presented in Table 5.1:

**Table 5.1:** Definition of dependent and independent variables

| **Abbreviation** | **Measure** | **Variable** |
|---|---|---|
| IR | Logged initial returns | Initial Return |
| ICO Price | Logged ICO price at offer | ICO price |
| RC | Funding Raised ($) | Raised Capital |
| ICO Duration | Duration between ICO start date to ICO end date (Days) | ICO Duration |
| Whitepaper | Dummy variable, level of competence ( (Hsieh & Oppermann, 2021) | Whitepaper |
| ETH | Dummy variable, platform. It takes value of 1 if the token was created on 'Ethereum Request for Comment' (ERC20) or 0 for any other platform type such as BEP2, NEO, STALLER, SOLONA or others | Ethereum platform |
| BCR | Logged return on Bitcoin for the same period | Bitcoin Return |
| ER | Logged return on Ethereum for the same period | Ethereum Return |
| BTS | Dummy variable, industry | Blockchain Tech services |
| ETM | Dummy variable, industry | Entertainment and media |
| Fintech | Dummy variable, industry | Finance |
| HTS | Dummy variable, industry | High Tech Services |
| MP | Dummy variable, industry | Marketplace |
| Other | Dummy variable, industry | Other small industries such as Real Estate, Health Care, etc. |
| Pandemic | Dummy variable, Time. It takes value of 1 if ICO was listed after March 11, 2020, else 0 | Pandemic |
| HPR | Logged holding period returns for several holding periods | Holding period return |
| ICO Listing Price | Logged ICO listing price at the close of first trading day | ICO Listing price |
| ICO Listing Duration | Duration between ICO end date to ICO Listing date (Days) | ICO Listing Duration |

Similarly, for our second set of analysis our main goal is to understand whether the returns to ICO investors are reversed after tokens are traded in the market, as it happens to the stocks after their initial public offerings (Hsieh & Oppermann, 2021). Moreover, we also intend to examine any changes in the significance of industry component and pandemic dummy on 180 and 365-days holding period returns for secondary investors. Hence, to examine the effect on the industry variable and the pandemic variable we have established the model 4 as below:

$$\begin{aligned} HPR_i = \alpha + \beta_1 log(ICOListingPrice_i) + \beta_2 log(RC_i) + \beta_3 ICOListingDuration_i \\ + \beta_4 Whitepaper_i + \beta_5 ETH_i + \beta_6 BCR_i + \beta_7 ER_i + \beta_8 BTS_i + \beta_9 ETM_i \\ + \beta_{10} Fintech_i + \beta_{11} MP_i + \beta_{12} HTS_i + \beta_{13} Others_i + \beta_{14} Pandemic_i + \epsilon_i \end{aligned} \tag{5.4}$$

# 6 Analysis

There were, in total, 1,103 observations collected from ICOdrops.com. These 1,103 observations included both alive and dead ICOs. After filtering these ICOs based on their availability of additional information through websites, we found that only 993 observations had some sort of additional information. These 993 observations were, hence, considered to be alive and were included for further analysis. Of those 993 observations, 53 were listed before the start of ICO either due to pre-sale, an earlier offering or a conversion and thus were excluded leaving us with 940 ICOs. We have further filtered out observations where we lacked enough information to carry out our required initial and holding period analysis. However, for descriptive statistics presented in Table 6.1 we have considered a different set of observation based on the available information.

## 6.1 Descriptive analysis of ICO characteristics

Table 6.1 provides descriptive statistics of our broad sample. The descriptive statistics gives us a numeric overview and comparison of the variables in our regression model. In our broader sample, we had 940 observations which were either identified as listed or not listed. The mean value of 0.8851 shows that majority of observations in our sample were listed.

**Table 6.1:** Descriptive statistics of overall sample

| **Variables** | **Observation** | **Mean** | **Median** | **SD** | **Max** | **Min** |
|---|---|---|---|---|---|---|
| Listed/Non-listed | 940 | .8851 | 1 | 0.3191 | 1 | 0 |
| Capital Raised ($ mil) | 857 | 14.0712 | 3.57 | 64.5731 | 1681.16 | 0.01 |
| ICO Price ($) | 827 | 10.3945 | 0.095 | 228.988 | 6500.00 | 0.000000132 |
| ICO Duration (days) | 904 | 8.7467 | 2 | 29.437 | 398 | 0* |
| Listing Duration (days) | 825 | 36.5588 | 5 | 103.1628 | 1138 | $0^{+}$ |
| ETH (dummy) | 918 | .79 | 1 | 0.4061 | 1 | 0 |
| Whitepaper (dummy) | 884 | .79 | 1 | .4086 | 1 | 0 |

Note: *Implies that ICO duration was less than 1 day. +Implies that ICOs were listed on the same day when they were offered for sale

Similarly, 91% of the 940 ICOs had non-zero and non-missing values for capital raised. The remaining 9% of ICOs likely fall into one of the four categories: (1) They raised capital and used it to continue with the project, but did not announce the amount raised, (2) they raised capital but did not reach their 'softcap', the minimum funding required to go through with the project, so they refunded the funds to investors, (3) they were scams used to collect funds and later fled with the investors' money and (4) they announced their ICOs but never actually took place (Hsieh & Oppermann, 2021). The average ICO raised \$14.07 million, but the distribution is positively skewed due to a small number of 'mega-ICOs' as the median value raised was only \$3.57 million. Overall, approximately 88% of the total 940 observations had ICO price information. For those 827 observations with ICO price information, the mean ICO price was \$10.40 with a larger standard deviation of 228.98 which looked reasonable considering the outlier maximum ICO price of \$6500.

The average length of ICO, ICO duration, for 904 observations was 8.75 days. This average is less when we look at similar descriptive statistics for different sub-groups later in this section. Similarly, the mean listing duration which measures the average time for the ICO to be listed on an exchange was 36.56 days. Again, this average was pulled down, for the whole sample, mainly due to a huge reduction in ICO listing time in the post-Covid sub-group. For this broader sample, the mean value for ETH dummy and Whitepaper dummy was 0.79 which implies that the majority of the ICOs observed were built on the ECR20 platform and had published some sort of information in their whitepaper before the ICO issue.

**Table 6.2:** Descriptive statistics for different sub-groups

| Subsamples | All usable sample | Listed = 1<br>Pre-covid = 1 | Listed =1<br>Post covid =1 | Listed = 0<br>Post-covid = 1 |
|---|---|---|---|---|
| | Mean | | | |
| | (Median) | | | |
| | [observation] | | | |
| ICO Duration (days) | 8.7467<br>-2<br>[904] | 16.01<br>-3<br>[221] | 5.29<br>-1<br>[582] | 13.04<br>-3<br>[99] |
| ICO Price ($) | 10.3945<br>-0.095<br>[827] | 0.77<br>-0.05<br>[210] | 3.26<br>-0.1<br>[552] | 105.29<br>-0.15<br>[63] |
| Listing Duration (days) | 36.5588<br>-5<br>[825] | 88.72<br>-24.5<br>[228] | 16.66<br>-2<br>[595] | |
| Capital Raised ($ mil) (>0) | 14.0712<br>-3.57<br>[857] | 22.24<br>-15<br>[223] | 8.12<br>2.4<br>[548] | 31.16<br>-2.58<br>[85] |
| ETH (dummy) | 0.79<br>-1<br>[918] | 0.82<br>-1<br>[215] | 0.77<br>-1<br>[595] | 0.85<br>-1<br>[106] |
| Whitepaper(dummy) | 0.79<br>-1<br>[884] | 0.94<br>-1<br>[181] | 0.78<br>-1<br>[595] | 0.57<br>-1<br>[106] |

Hsieh and Oppermann (2021) had classified the post-February 2018 period as 'Bear Market Period' for ICO. Thus, it would be reasonable to assume that ventures, considering the bearish trend of the market, maintained longer issue period to collect their target capital through ICOs. Thus, Table 6.2, unsurprisingly, shows that the ICO duration for pre-Covid listed ICOs (16.01 days) was three times higher than the post-Covid listed ICO duration (5.29 days). While the ICO duration for post-Covid non-listed ICOs was 13.04 days. Similarly, the average ICO price for post-Covid listed ICOs was much higher than pre-Covid listed ICOs, this can be inferred as an increased level of venture's awareness about the investors' interests in such tokens or increased trust of investors in the venture's technology and development plan. However, the average capital raised by post-Covid listed ICOs was much smaller at $8.12 million which can be due to smaller number of ICO offerings at higher prices or merely due to larger number of observations for the post-Covid ICOs.

As previously highlighted, the average listing duration for the pre-Covid ICO was much larger at 88.72 days compared to 16.66 days for the post-Covid listed ICOs. Such a decrease in listing days can be due to the increasing number of exchanges available for ICOs' listing and increased standardization of the ICO listing process made available by exchanges like CMC. We can observe a decrease in average for the ETH dummy for the post-Covid listed ICOs compared to the pre-Covid ICOs. This was mainly due to the introduction of new platforms like SOLONA, NEO and due to the increasing number of ventures that were built on their own platform. Whereas the average for whitepaper dummy decreased for post-Covid ICOs compared to pre-Covid ICOs. This decrease can indicate less significance of the whitepaper as an indicator of technical affluence of the ventures. This whitepaper dummy has been used in the regression model to examine its effect on the initial returns and the holding period returns which is discussed later.

In Table 6.3, we present the descriptive statistics for ICO characteristics for different industries. We also incorporate the pre-Covid and the post-Covid sub-groups to explore any changes in these two periods. Only listed ICOs were included while preparing the following descriptive summary.

**Table 6.3:** Descriptive statistics based on industry category

| 0 ->pre-covid | | ICO Duration (days) | | ICO Price ($) | | Listing Duration (days) | | Capital Raised ($ mil) (>0) | | ETH (dummy) | | Whitepaper (dummy) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 ->post covid | | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| BTS | Mean | 14.05 | 4.5 | 0.31 | 1.15 | 88.75 | 17.13 | 23.79 | 14.09 | 0.8 | 0.79 | 0.97 | 0.73 |
| | SD | 31.95 | 9.93 | 1.69 | 7.75 | 156.7 | 36.35 | 38.85 | 54.59 | 0.4 | 0.41 | 0.17 | 0.44 |
| HTS | Mean | 13.91 | 6.27 | 0.29 | 6.93 | 136.82 | 16.82 | 20.5 | 6 | 0.88 | 0.79 | 0.93 | 0.8 |
| | SD | 28.33 | 34.99 | 0.72 | 75.56 | 256.89 | 40.37 | 31.32 | 10.74 | 0.34 | 0.41 | 0.26 | 0.4 |
| Fintech | Mean | 9.97 | 8.48 | 4.03 | 3.28 | 38.52 | 23.97 | 22.73 | 5.48 | 0.84 | 0.85 | 0.85 | 0.75 |
| | SD | 12.11 | 44.52 | 19.99 | 12.22 | 52.52 | 57.76 | 23.46 | 9.13 | 0.37 | 0.36 | 0.37 | 0.44 |
| ETM | Mean | 37.63 | 2.67 | 0.02 | 0.32 | 211.5 | 11.77 | 18.05 | 5.61 | 0.75 | 0.65 | 1 | 0.86 |
| | SD | 54.86 | 3.62 | 0.03 | 1.55 | 387.12 | 53.41 | 6.8 | 14.41 | 0.46 | 0.48 | 0 | 0.35 |
| MP | Mean | 13.93 | 6.36 | 0.13 | 0.31 | 49.47 | 13.29 | 14.24 | 2.38 | 0.86 | 0.71 | 1 | 0.71 |
| | SD | 15.74 | 11.53 | 0.15 | 0.48 | 64.06 | 21.21 | 9.69 | 1.79 | 0.36 | 0.46 | 0 | 0.46 |
| Others | Mean | 38.13 | 2.47 | 0.21 | 1.96 | 65.25 | 14.8 | 23.25 | 14.08 | 0.87 | 0.8 | 0.92 | 0.67 |
| | SD | 81.16 | 1.92 | 0.33 | 4.17 | 91.25 | 36.04 | 17.92 | 23.86 | 0.35 | 0.41 | 0.29 | 0.49 |

From Table 6.3 we can observe that the ICO duration for all industry, except for ventures in Fintech, category have decreased remarkably. The mean ICO prices for Fintech have decreased while the mean ICO prices for other industry categories have increased. Moreover, the listing duration of the post-Covid ICOs has decreased irrespective of the industry categorization. Not surprisingly, the average capital raised in all industry segments has decreased in the post-Covid period. It can be indicative of the economic effects of the pandemic on the crypto market. This relationship was tested in a multivariate regression model where we used pandemic as a control variable.

Ethereum's ERC20 platform was less popular in entertainment, marketplace and other sectors as observed by the reduced mean value for the post-Covid listed observation. While ERC20 platform was still relevant for BTS, HTS and Fintech sectors as observed by the mean values for the pre-Covid and the post-Covid observations. Finally, looking at the mean value of Whitepaper dummy, we can conclude that the popularity of whitepaper issuance post-Covid was degrading across all industries.

## 6.2 Descriptive analysis of Initial Returns

Although we had 904 observations with some information about the ICO characteristics, our sample was narrowed down to 684 observations for the initial return analysis. Table 6.4 presents the summary statistics for the ICO characteristics and the initial returns for these 684 observations under the pre-Covid and the post-Covid sub-groups.

**Table 6.4:** Descriptive statistics of listed ICOs for pre-covid and post-covid subgroups

| Subsamples | All usable sample | Listed = 1<br>Pre-covid = 1 | Listed =1<br>Post covid =1 |
|---|---|---|---|
| | Mean | | |
| | (Median) | | |
| | [observation] | | |
| ICO Duration (days) | 6.99 | 13.78 | 4.32 |
| | -1.5 | -33.31 | -1 |
| | [684] | [193] | [491] |
| ICO Price ($) | 2.73 | 0.81 | 3.49 |
| | -40.78 | -0.05 | -0.1 |
| | [684] | [193] | [491] |
| Listing Duration (days) | 37.72 | 89.24 | 13.29 |
| | -5 | -24 | -2 |
| | [684] | [193] | [491] |
| Capital Raised ($ mil) (>0) | 11.8 | 20.897 | 8.23 |
| | -3.67 | -15 | 2.58 |
| | [684] | [193] | [491] |
| Log Raw Initial Return | 1.008 | 0.076 | 1.374 |
| | -0.922 | -0.17 | -1.327 |
| | [684] | [193] | [491] |
| Log BitCoin Adj. Initial Return | 1.004 | 0.092 | 1.363 |
| | -0.949 | -0.207 | -1.335 |
| | [684] | [193] | [491] |
| Log ETH Adj. Initial Return | 1.029 | 0.213 | 1.35 |
| | -0.974 | -0.31 | -1.329 |
| | [684] | [193] | [491] |
| Log Raw Listing Day Return | 0.046 | -0.0086 | 0.0678 |
| | (-0.015) | (-0.0145) | (-0.0152) |
| | [684] | [193] | [491] |
| Log BitCoin Adj. Listing Day Return | 0.047 | -0.0114 | 0.0701 |
| | (-0.020) | (-0.0209) | (-0.02) |
| | [684] | [193] | [491] |
| Log ETH Adj. Listing Day Return | 0.047 | -0.0103 | 0.0689 |
| | (-0.022) | (-0.0231) | (-0.02) |
| | [684] | [193] | [491] |

From Table 6.4, we can observe that the ICO duration, the listing duration and the raised capital have decreased for the post-Covid sample. The average IPO price for the post-Covid sample was $3.49 (median was $0.1) compared to $0.81 (median was $0.05) for the pre-Covid sample, suggesting a positive drift in the price between the pre-Covid and the post-Covid times. Calculating the rate of return for the sample where the ICO price and the opening market prices were available yields an average rate of return of 100.8% (the median rate of return was 92.2%). This initial return varied between two sub-groups.

The post-Covid initial returns were 137.4% compared to 7.6% for the pre-Covid sample. Further, calculating the rate of return for the ICOs within the first day of listing using the listing day close and open price, we found that ICOs yield for the first listing day was 4.6%. The listing day returns also varied between two sub-groups. Interestingly, the pre-Covid sub-group averaged a negative (-0.86%) listing day returns while it was positive for the post-Covid sub-group at 6.78%. Although, the average listing day returns for the post-Covid sub-group was positive, the median value was negative at -1.52% suggesting that some of the ICOs were delivering very high first day returns.

The raw initial returns for the pre-Covid ICOs were less compared to the initial returns when adjusted for BitCoin and Ethereum returns during the same ICO ending time and listing time. We can think of this as an initial abnormal return adjusted for the cryptocurrency market. The initial abnormal return for the pre-Covid ICOs averaged at 9.2% and 21.3% after adjusting for Bitcoin and Ethereum returns, respectively. While such a huge difference in the initial abnormal returns was not observed for the post-Covid ICOs. Similarly, the listing day abnormal return was more negative for the pre-Covid ICOs compared to the listing day raw returns. Whereas for the post-Covid listing day returns, there was a marginal change in the market adjusted abnormal returns compared to the raw returns.

**Table 6.5:** Descriptive statistics for returns across industry

| 0 ->pre-covid | | Log Raw Initial Return | | Log Raw Listing Day Returns | | Log BitCoin Adj.Initial Return | | Log ETH Adj. Initial Return | | Log BitCoin Adj. Listing Day Return | | Log ETH Adj. Listing Day Return | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 ->post covid | | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| BTS | Mean | 0.274 | 1.374 | -0.0002 | 0.099 | 0.242 | 1.353 | 0.373 | 1.34 | -0.003 | 0.107 | -0.003 | 0.103 |
| | SD | 1.935 | 1.322 | 0.157 | 0.61 | 2.022 | 1.321 | 2.028 | 1.309 | 0.163 | 0.62 | 0.152 | 0.62 |
| HTS | Mean | 0.162 | 1.277 | -0.045 | 0.115 | 0.158 | 1.27 | 0.231 | 1.252 | -0.035 | 0.117 | -0.034 | 0.115 |
| | SD | 1.446 | 1.849 | 0.24 | 1.322 | 1.439 | 1.873 | 1.38 | 1.869 | 0.223 | 1.321 | 0.219 | 1.323 |
| Fintech | Mean | -0.203 | 0.898 | -0.033 | 0.064 | -0.129 | 0.879 | -0.036 | 0.876 | -0.038 | 0.062 | -0.029 | 0.061 |
| | SD | 1.752 | 1.175 | 0.166 | 0.508 | 1.731 | 1.211 | 1.712 | 1.222 | 0.183 | 0.509 | 0.175 | 0.5 |
| ETM | Mean | 0.277 | 1.839 | -0.0425 | -0.046 | 0.08 | 1.834 | 0.196 | 1.829 | -0.045 | -0.045 | -0.038 | -0.04 |
| | SD | 1.864 | 1.939 | 0.133 | 1.262 | 1.268 | 1.927 | 1.093 | 1.929 | 0.17 | 1.261 | 0.16 | 1.26 |
| MP | Mean | -1.109 | 1.338 | 0.126 | 0.013 | -0.939 | 1.327 | -0.758 | 1.307 | 0.118 | 0.007 | 0.121 | 0.009 |
| | SD | 1.768 | 1.243 | 0.26 | 0.189 | 1.684 | 1.223 | 1.612 | 1.239 | 0.263 | 0.19 | 0.264 | 0.192 |
| Others | Mean | -0.586 | 1.236 | -0.011 | 0.074 | -0.336 | 1.252 | -0.133 | 1.228 | -0.027 | 0.073 | -0.027 | 0.067 |
| | SD | 1.647 | 1.431 | 0.2154 | 0.438 | 1.561 | 1.423 | 1.413 | 1.431 | 0.211 | 0.433 | 0.207 | 0.429 |

From Table 6.5 we can observe that the log raw initial returns across all industries averaged higher and positive for the post-Covid sample, whereas we observe that ventures in Fintech, MP and Other averaged a negative raw initial return for the pre-Covid sample. Not surprisingly, except MP sectors, the average raw listing day return for the pre-Covid sample was negative. We found it not surprising because the MP sector was highly underpriced when their ICOs were listed in the exchange for trading represented by the high negative mean value of -1.109. Moreover, we also observe that the ETM was the only industry category that averaged a negative listing day raw return during the post-Covid period. The high standard deviation value across these industries and pandemic period suggests that the returns in ICOs are very volatile which is understandable as crypto markets, in general, are considered very risky investments.

These descriptive statistics of initial returns seem consistent with our assumptions that the pandemic and the industry characteristics can contribute to different initial returns for the investors.

## 6.3 Descriptive statistics of Holding Period Returns (HPR)

The following section provides a descriptive statistic of holding period returns for different holding periods across different industry segments. We have presented the average value in the first row and the number of observations in the second row with square brackets "[n]".

In Table 6.6, we can observe that the holding period returns across all the industries are negative for both the pre-Covid and the post-Covid periods. For the pre-Covid period, all industries reported degrading returns as the holding period increased. Whereas for the ICOs that fall under the post-Covid sub-group, the holding period returns have increased negatively as the holding period increases from 1-day to 90-days across all industries. Moreover, the holding period returns for 180- and 365-days showed a higher negative average value for the ventures that belong to ETM (entertainment and media), MP (marketplace) and HTS (high-tech services) industry. While 180- and 365-days holding period returns for ventures in BTS have improved but were still negative.

**Table 6.6:** Descriptive statistics of holding period return across industry

| | HPR_1 Days | | HPR_7 Days | | HPR_14 Days | | HPR_30 Days | | HPR_90 Days | | HPR_180 Days | | HPR_365 Days | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| BTS | -0.004 | -0.11 | -0.09 | -0.05 | -0.192 | -0.125 | -0.41 | -0.326 | -0.86 | -0.7 | -1.3 | -0.64 | -1.68 | -0.29 |
| | [100] | [135] | [99] | [135] | [99] | [128] | [99] | [128] | [99] | [116] | [99] | [72] | [98] | [29] |
| HTS | -0.039 | -0.105 | -0.068 | -0.155 | -0.113 | -0.226 | -0.33 | -0.342 | -0.793 | -0.826 | -1.3 | -0.83 | -1.53 | -1.59 |
| | [32] | [171] | [32] | [170] | [32] | [167] | [31] | [165] | [31] | [154] | [31] | [114] | [31] | [56] |
| Fintech | -0.019 | -0.014 | 0.025 | -0.052 | -0.036 | -0.104 | -0.23 | -0.242 | -0.769 | -0.556 | -1.39 | -0.38 | -1.59 | -0.89 |
| | [28] | [56] | [28] | [56] | [28] | [56] | [28] | [55] | [28] | [52] | [28] | [48] | [28] | [35] |
| ETM | -0.033 | -0.081 | -0.105 | -0.171 | -0.217 | -0.195 | -0.46 | -0.478 | -0.906 | -1.348 | -1.79 | -0.51 | -1.6 | 1.09 |
| | [8] | [98] | [8] | [97] | [8] | [91] | [8] | [88] | [8] | [67] | [7] | [14] | [7] | [6] |
| MP | -0.109 | -0.105 | -0.106 | -0.032 | -0.298 | -0.171 | -0.45 | -0.231 | -1.115 | -0.488 | -1.43 | -0.3 | -1.71 | -0.93 |
| | [10] | [20] | [10] | [20] | [10] | [20] | [10] | [20] | [10] | [20] | [10] | [14] | [10] | [3] |
| Others | -0.0002 | -0.142 | -0.009 | -0.26 | -0.191 | -0.292 | -0.33 | -0.605 | -0.539 | -1.216 | -1.32 | -1.33 | -2.21 | -1.72 |
| | [15] | [11] | [15] | [11] | [15] | [11] | [15] | [11] | [15] | [11] | [15] | [9] | [15] | [6] |

Note: Value in square brackets "[n]" represents number of observations

## 6.4 The Regression results

### 6.4.1 Regression model for initial returns

Table 6.7 provides the main results of our study. It presents the estimated coefficients and standard error (in parentheses) from cross-sectional regression using OLS. We also present the number of observations, R-squared values, and adjusted R-squared values of the models at the bottom three rows of Table 8. The dependent variable in all the regression model in Table 6.7 is the natural logarithm of the ratio of the first day's opening price of token to its ICO offering price. Moreover, the regression model fitted are numbered from 1 to 7 (presented in column of Table 6.7) and uses different independent variables in the regression for the ICO initial returns.

In Model 1, we examine the effects of the ICO characteristics variables on the ICO initial returns. The main reason behind this regression model was to verify the assumption that the ICO characteristics influence the ICO initial returns. From Model 1, we can see that all the independent variables are significant at different level of significance. Specifically, we found that the logged ICO price and the logged raised capital influences the ICO initial returns negatively and were significant at 0.1% level. The coefficient for the log-ICO price is negative at -0.1239, suggesting that a 1 percentage point increase in the ICO price decreases the ICO initial returns by 12.39 percentage points, ceteris paribus. Similarly, a 1 percentage point increase in the ICO raised capital decreases the ICO initial returns by 17.85 percentage points, ceteris paribus. Moreover, longer ICO duration of more than one week negatively affected the ICO initial returns with a coefficient value of -0.40 which was also significant at 5% level. The adjusted R-squared of Model 1 is 0.0227 which implies that the explanatory power of the independent variable under consideration is very low.

In Model 2, we test whether the availability of whitepaper during token sales, including the ICO characteristics variable from Model 1, has any effect on the ICO initial returns. We found that the issuance/availability of whitepaper has no significant effect on the ICO initial returns. After including the whitepaper dummy, the ICO duration still shows a negative effect on the initial returns but was no more significant. However, the effect of the ICO price and the ICO raised capital were still significant and negative. We also notice that the coefficient for the log ICO price increased from -0.1239 (in Model 1) to -0.1364 (in Model 2). Whereas the coefficient for the log ICO price decreased from -0.1785 (in Model 1) to -0.1567 (in Model 2).

**Table 6.7:** Cross sectional determinants of ICO initial returns

| ICO_Initial Returns (log) | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| **Constant** | 1.0089 ***<br>(0.1191) | 1.18062***<br>(0.18198) | 1.45288***<br>(0.22564) | 1.37522***<br>(0.25321) | 1.30204***<br>(0.2219) | 1.162551***<br>(0.2162) | 1.22456***<br>(0.2424) |
| **ICO Characteristics** | | | | | | | |
| Log_ICO_price | -0.1239***<br>(0.0304) | -0.1364***<br>(0.0309) | -0.13269***<br>(0.0312) | -0.1249***<br>(0.0312) | -0.1475***<br>(0.0306) | -0.19452***<br>(0.0305) | -0.18254***<br>(0.0308) |
| Log_Raised Capital | -0.1785 ***<br>(0.0407) | -0.1567***<br>(0.0414) | -0.14978***<br>(0.0415) | -0.13035**<br>(0.0424) | -0.11909**<br>(0.0411) | -0.005617<br>(0.0435) | -0.01066<br>(0.0438) |
| ICO_Duration:<br>More than week | -0.40037*<br>(0.1726) | -0.28952<br>(0.1822) | -0.31200+<br>(0.1838) | -0.26165<br>(0.1834) | -0.26049<br>(0.1797) | -0.115399<br>(0.1757) | -0.09915<br>(0.1760) |
| Whitepaper dummy:<br>Yes | | -0.2613<br>(0.1824) | -0.23331<br>(0.1831) | -0.30084*<br>(0.1826) | -0.16739<br>(0.1792) | -0.059129<br>(0.1746) | -0.09778<br>(0.1758) |
| ETH dummy: Yes | | | -0.35428*<br>(0.1636) | -0.25695<br>(0.1647) | -0.27789*<br>(0.1603) | -0.226444<br>(0.1556) | -0.16647<br>(0.1574) |
| Industry dummies | | | | | | | |
| ETM | | | | 0.57170**<br>(0.2104) | | | 0.28566<br>(0.2044) |
| FINTECH | | | | -0.39060*<br>(0.2250) | | | -0.38961+<br>(0.2149) |
| HTS | | | | 0.08595<br>(0.1721) | | | -0.12727<br>(0.1664) |
| MP | | | | -0.27749<br>(0.3454) | | | -0.31295<br>(0.3293) |
| OTHERS | | | | -0.36495<br>(0.3856) | | | -0.14861<br>(0.3714) |
| Control Variable | | | | | | | |
| BitCoin return (log) | | | | | -2.32745***<br>(0.5251) | -1.544527**<br>(0.52331) | -1.63545**<br>(0.5239) |
| Ethereum return (log) | | | | | 2.10866***<br>(0.3681) | 1.481298***<br>(0.3697) | 1.50888***<br>(0.3691) |
| Pandemic dummy:<br>pre-covid | | | | | | -1.16053***<br>(0.1794) | -1.09040***<br>(0.1844) |
| Observations | 684 | 659 | 649 | 649 | 649 | 649 | 649 |
| R-squared | 0.0269 | 0.07027 | 0.07791 | 0.1013 | 0.1234 | 0.1772 | 0.1885 |
| Adjusted_R-squared | 0.0227 | 0.06459 | 0.07074 | 0.0872 | 0.1138 | 0.1669 | 0.1718 |

Significance levels: + $p < 0.10$ , * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Values in parentheses refer to the standard error value. The chronological numbers in the column headings are regression model numbers.

In Model 3 we test the effect of all the ICO characteristics variables- log ICO price, log ICO capital raised, ICO duration, whitepaper dummy and ETH dummy- on the ICO initial returns. Specifically, we add the ETH dummy to our existing Model 2. This dummy variable takes a value 1 if the venture, issuing the ICO, uses ERC20 platform. We can observe that using the ERC20 platform (ETH dummy in our model 3) negatively affected the ICO initial returns at 5% level of significance. The coefficient of the ETH dummy is -0.3543 suggesting that the ICO initial returns for the ventures that used the ERC20 platform was 35.43 percentage points less than the ventures that did not used the ERC 20 platform. In other words, the ventures that used other platforms, not the ERC20, registered higher initial returns. The ERC20 platform is a standard platform used by different ventures and owned by Ethereum. Thus, the investors believe the technical affluence of those ventures which are built on the ERC20 platform which explains these lower initial returns. After including the ETH dummy, the ICO duration still showed a negative effect on the initial returns, but at 10% significance level. Moreover, the effect of the ICO price and the ICO raised capital were still negative and significant at 0.1% level. While the whitepaper issuance/availability had no significant effect on the ICO initial returns.

Model 4 combines the independent variables from Model 3 with industry category variable, a binary variable. Industry category represents different industries, namely, BTS, ETM, FINTECH, HTS, MP and others. The value of the constant, in Model 4, represents those ventures that operated under the BTS industry. After including industry dummies, the coefficients for the ICO price and the ICO raised capital were still negative. However, the level of significance for the ICO raise capital variable dropped to 1%, which was 0.1% until Model 3. While the ICO price was still significant at 0.1% level. In Model 4, we can observe that the whitepaper dummy was significant at 5% level, which implies that investors consider the issuance of whitepaper availability as an important determinant for the ICO initial returns, in the BTS sector. Furthermore, two industry categories namely ETM and FINTECH affected the ICO initial return positively (at 1% level of significance) and negatively (at 5% level of significance), respectively. The coefficient of ETH is 0.5717 which implies that the investors who invested in the ICOs of the ETM sector managed to gain 57.17% higher initial returns than those investors who invested in the BTS sector.

In Model 5, we introduced our control variable that captures the effect of the cryptocurrency market. We combine the independent variable from the Model 3 with two control variables- Bitcoin and Ethereum log returns. We have used Bitcoin and Ethereum log return for the same period, i.e., the natural logarithm of the ratio of the Bitcoin price on the listing day of the token to the Bitcoin price on the ICO end date. We found that both the Bitcoin returns and the Ethereum returns have statistically significant effect on the ICO initial returns at 1% level. However, the coefficient for Ethereum was positive at 2.11 but it was negative for Bitcoin at -2.33. This implies that the positive movement in Bitcoin prices decreased the initial returns of the ICOs while the positive movement in Ethereum prices increased the initial return of the ICOs. After including the control variables, the coefficients for the ICO price and the ICO raised capital were still negative. However, the level of significance for the ICO raise capital variable dropped to 1%, which was 0.1% until Model 3. While the ICO price was still significant at 0.1% level. Similarly, the ETH dummy was also significant at 5% level. The adjusted R-squared of Model 5 is 0.1138, which can be perceived as a reasonable fit where the independent variables have some explanatory power.

Model 6 includes one additional control variable to Model 5. In Model 6, we introduce the pandemic dummy as the additional control variable. This regression model intends to test the effect of the pandemic on the ICO initial returns. We observe that the coefficient for the pandemic dummy is significant at 0.1% level. The negative coefficient of the pandemic dummy implies that the initial return of ICO that ended before March 11, 2020, had 116.05% less initial returns compared to those ICOs that ended after March 11, 2020, other things remaining the same. Whereas, among the variables that represented the ICO characteristics, only the ICO price was still found to be significant. After controlling for the pandemic, the effect of Bitcoin returns and Ethereum returns were still significant but at the lower coefficient values. This implies that some of the effects of Bitcoin and Ethereum returns on the ICO initial returns was due to the pandemic, which also affected the entire cryptocurrency market. The adjusted R-squared of Model 6 is 0.1669, which can be perceived as a better fit compared to Model 5.

Finally, Model 7 is our unrestricted model estimated in equation 3. Model 7 includes all the variables from Model 6, in addition to binary variable that resembles the ventures' operating industry. In Model 7, except for the ICO price, all other ICO characteristics variables are insignificant. These negative coefficient for the ICO price is -0.1825 and thus indicates that the estimated initial return of the ICO decreases by 18.25 percentage points if the ICO prices increased by 1 percentage points, ceteris paribus. Moreover, none of the industry dummies are significant at 5% level. Thus, the industry in which the venture operates does not substantiate an indication of effect.

Furthermore, the pandemic control variable is still significant at 1% -level and strongly indicates that the pandemic dummy's impact on the ICO initial returns. The coefficient is negative at -1.0904, slightly less than Model 6, implying that ICOs that were listed and traded before the pandemic have 109.04 percentage points lower estimated initial returns than the ICOs that were listed and traded after the pandemic. In addition, the clear influence of Bitcoin and Ethereum on the token return is still substantiated, like Model 6. The adjusted R-squared of Model 7 is 0.1718, which still indicates that some variations in the ICO initial returns are explained by the included variables and that the goodness of fit is at an acceptable level.

### 6.4.2 Discussion of cross-sectional effects on initial returns

As presented above, we can see that the ICO price is the only independent variable, out of 5 ICO characteristics variables, that has a statistically significant effect on the initial returns of ICOs. In our unrestricted model (Model 7), the log ICO prices have a negative coefficient (-0.1825) and a significant impact on the log ICO initial returns. This indicates that the investors' initial returns for their investment in ICOs depend on the price they pay when they bought those tokens. The investors that pay 1 percentage point less for the ICO are likely to realize 18.25 percentage points higher initial returns, ceteris paribus. The intuition behind this finding is that the lower ICO price generates higher demand for such low-priced tokens which evidently signify higher popularity and liquidity once the tokens are listed. Moreover, such popularity triggers a herd behavior, which is common in the speculative market like crypto currency, that ultimately results in higher listing prices for the tokens and consequently higher initial returns for the initial investors. Our finding is also coherent with the findings from Benedetti and Kostovetsky (2021), who argued that the ICO investors generated higher initial returns relative to the ICO prices for those ICO which were offered for lower nomial price.

Moreover, in our unrestricted model, we found that the amount raised during the ICO had no significant influence on the initial returns which was consistent with the findings of Hsieh and Oppermann (2021). However, this finding deviates from what Benedetti and Kostovetsky (2021) found in their study. Benedetti and Kostovetsky (2021) highlighted that there existed higher demand for low priced ICOs which consequently suggests higher raised capital. Based on our findings, we coincide with the idea that the low priced ICOs generate higher demand which most likely should generate higher capital. However, the higher capital raised seems not to manifest in the initial returns. Contrary to Benedetti and Kostovetsky (2021) who found a positive effect of the raised captial on the ICO initial returns, we found that, the raised capital has negative effects on the ICO initial returns, based on Model 5. We argue for our findings on the two major grounds: time horizon and speculative nature of the cryptocurrency market. The observations in this thesis cover the time period from January 2018, to March 2020. This period was the bear-period in the cryptomarket and the period of high economic uncertainty due to Covid. Investors in cryptomarket are speculative investors who seek for short-term gains. Such speculative investors are least concerned about the progress of the acutal venture, especially in a bearish and uncertain period. Hence, their investments are more for speculative gains rather than longterm value creation. Therefore, based on our findings, we suggest that ICO prices are the only ICO characteristic variables that speculative investors consider while considering the initial returns.

The ICO duration had significant effect on the ICOs' initial return in Model 1. However, the significance did not exist once we introduced the control variables. One can think of this as the effect of control variable, however there can be another explanation for it. Hsieh and Oppermann (2021) also studied the effect of ICO duration on the ICOs' initial returns. They went on to cateroize the ICOs with duration shorter than 21 days, as short duration ICOs and all other ICOs as long duration ICOs. They found that the effect of the ICO duration on the initial returns depended on the length of the duration. They concluded that for the short-duration ICOs, having fewer days of ICO period would increase their initial returns while if the ICO duration was long, then having fewer or more days would have no effect. Since, we have considered all ICOs having more than 7 days as long-duration ICO our result to some extent coincides with Hsieh and Oppermann (2021). Having said that, we cannot disregard the effect of control variable could be another explanation for the insignificant outcome.

Furthermore, we found that the ventures operating in certain industries evidently do not affect the initial returns. Intitutively, we can argue that the firm-specific product or services are of more interest to the investors but not the industries. All ICOs fall under a larger blockchain industry. Thus, this broader industry-specific variations might have higher implications during the pre-Covid and the post-Covid period. Therefore, based on our findings we cannot establish any significant effect of the industry category dummy on the ICO initial returns. However, this finding contradicts with the finding of Hsieh and Oppermann (2021) who found that ICOs related to the high-tech services and the platform products had significantly higher initial returns.

Finally, we found that the cryptocurrency market returns and the pandemic had significant effect on the ICO initial returns. The finding related to the cryptocurrency market was coherent with the finding of Hsieh and Oppermann (2021) who also reported significant influence of the cryptocurrency market represented by Bitcoin and Ethereum on the ICO initial returns. While for pandemic we do not have any similar study to relate our study with; thus, based on our findings we conclude that the ICOs that ended before March 11, 2020 registered lower initial returns compared to the ICOs that ended after March 11, 2020. One of the possible explantion for this could be inferred from the previous studies of Benedetti and Kostovetsky (2021), and Fisch (2019) where they argued that the ICO market was at boom during 2017 with a huge amout of the ICO captial raised. Our data set includes ICO after 2018 where the market can be assumed to be at its saturation. Hence, we can conclude that the ICOs listed during 2018 to early 2020 registered lower initial returns. However, the ICOs that were listed after March 2020 registered higher initial returns. We argue that the possible reasons for such higher post-Covid initial returns may be due to the degrading capital markets caused by slow economic as nations instated lock downs. Furthermore, Covid disrupted the traditional routine of working individuals who, now, had ample time to learn and invest in crypto market which may be one of the many reasons for higher initial returns. Although our analysis suggests a larger initial return but we believe that these higher returns came at the cost of naïve investors who were merely trying to follow the herd of the hyped cryptomarket. Moreover, we also believe that diversion of funds from deteriorating capital market to cryptomarket was also influential for such post-Covid higher initial returns. Lastly, cryptomarket was marketed by some influential people through their investment and media presence which overstated the lucrative and speculative feature of dominant market benchmark currencies like Bitcoin and Ethereum which may have driven the initial returns of ICOs as well.

### 6.4.3 Regression model for 180-Days holding period returns

Table 6.8 presents the main results from our second analysis. It presents the estimated coefficients and standard error (in parentheses) from cross-sectional regression using OLS. We also present the number of observations, R-squared values, and adjusted R-squared values of the models at the bottom three rows of Table 6.8. The regression models estimated in Table 6.8 measure the effects of the independent variables on the cumulative token returns after 180 days of trading. The models are numbered from 1 to 7 and provide the results from regression with different sets of independent variables. It is noteworthy to mention, beforehand, that some of these regression models have a negative adjusted R-squared values that signify the insignificance of the explanatory variables used in those regression models. We could have completely disregarded those models; however, we choose to keep them for comparability.

**Table 6.8:** Cross sectional determinants of 180-days holding period returns

| ICO_180HPR (log) | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| Constant | -0.8898*** | -1.0582*** | -0.7657** | -0.8303** | -1.1641*** | -1.1141*** | -1.1318*** |
| | -0.1067 | -0.1867 | -0.2456 | -0.2763 | -0.2409 | -0.2395 | -0.2687 |
| ICO Characteristics | | | | | | | |
| Log_ICO_price | 0.032 | 0.0321 | 0.0288 | 0.0298 | 0.0111 | -0.0142 | -0.0129 |
| | -0.0269 | -0.0282 | -0.0284 | -0.0287 | -0.0274 | -0.0286 | -0.0289 |
| Log_Raised Capital | -0.0362 | -0.0335 | -0.0364 | -0.0264 | 0.0259 | 0.0679 | 0.07074 |
| | -0.0408 | -0.0423 | -0.0426 | -0.0437 | -0.0423 | -0.0444 | -0.0449 |
| ICO_ListingDuration: More than week | 0.09307 | 0.1079 | 0.1175 | 0.1271 | 0.3015* | 0.4161** | 0.4116** |
| | -0.1485 | -0.1542 | -0.1561 | -0.1607 | -0.151 | -0.1549 | -0.1585 |
| Whitepaper dummy | | 0.2295 | 0.2002 | 0.1908 | 0.1327 | 0.1803 | 0.1662 |
| | | -0.2018 | -0.204 | -0.2073 | -0.1939 | -0.1929 | -0.1977 |
| ETH dummy | | | -0.3220+ | -0.3265+ | -0.1819 | -0.1864 | -0.1726 |
| | | | -0.1879 | -0.1896 | -0.1775 | -0.176 | -0.1787 |
| Industry dummies | | | | | | | |
| ETM | | | | 0.1534 | | | 0.1633 |
| | | | | -0.3682 | | | -0.3419 |
| FINTECH | | | | 0.2834 | | | 0.0131 |
| | | | | -0.2158 | | | -0.2052 |
| HTS | | | | 0.0405 | | | -0.0051 |
| | | | | -0.1848 | | | -0.1746 |
| MP | | | | 0.1579 | | | 0.1816 |
| | | | | -0.3417 | | | -0.3189 |
| OTHERS | | | | -0.3586 | | | -0.1258 |
| | | | | -0.3587 | | | -0.3416 |
| Control Variable | | | | | | | |
| BitCoin return (log) | | | | | 0.4834* | 0.6077* | 0.5935* |
| | | | | | -0.233 | -0.2351 | -0.2413 |
| Ethereum return (log) | | | | | 0.3858* | 0.203 | 0.2168 |
| | | | | | -0.1691 | -0.1795 | -0.1818 |
| Pandemic dummy: pre-Covid | | | | | | -0.5918** | -0.5761** |
| | | | | | | -0.2074 | -0.2115 |
| Observations | 461 | 436 | 427 | 427 | 420 | 420 | 420 |
| R-squared | 0.00484 | 0.00662 | 0.01271 | 0.02112 | 0.1548 | 0.1712 | 0.1728 |
| Adjusted_R-squared | -0.00169 | -0.00259 | 0.00098 | -0.00241 | 0.1404 | 0.1551 | 0.1463 |

Significance levels: + $p < 0.10$ , * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: Values in parentheses refer to the standard error value. The chronological numbers in the column headings are regression model numbers.

In Model 1, we test the impact of the ICO characteristics variable on the 180-days HPR of the ICOs. The main idea behind this regression model was to verify the assumption that the ICO characteristics influence the 180-days HPR of the ICOs. We see that the adjusted R-squared of this model is negative which implies that the explanatory power of the independent variables, under consideration, is extremely low or negligible. In other words, the independent variables are insignificant to explain any relationship with the dependent variable.

Model 2 tests if the availability of the whitepaper, including the ICO characteristics variables from Model 1, has any effect on the tokens' 180-days HPRs. In Model 2, we regress 180-days log HPRs on the log ICO prices, the log raised capital, the ICOs' listing duration, and the whitepaper dummy, a binary variable. Again, we observe that Model 2 has a negative adjusted R-squared values. Hence, we can infer that availability of the whitepaper, including other independent variables, cannot explain the variation in the ICOs' 180-days HPR.

Model 3 adds another dummy variable to Model 2. This dummy considers for the platform technology that the venture plans to implement. In this model, we regress the ICOs' 180-days log-returns on the ETH dummy. We see that the ETH dummy is significant at 10% level, with a negative coefficient. This implies that the ventures that use the ERC20 platform have 32.20 percentage points lower estimated 180-days HPRs than those ventures that did not use the ERC20 platform. The adjusted R-squared of Model 3 is positive suggesting some explanatory power of the independent variables. However, the adjusted R-squared value is very low.

Model 4 combines the independent variables from Model 3 with industry category variable, a binary variable. Industry category represents different industries, namely, BTS, ETM, FINTECH, HTS, MP, and others. Specifically, Model 4 tests if the ventures operating in certain industries are more prone to 180-days capital gains. Since the adjusted R-squared value of Model 4 is negative, we can imply that the independent variables have negligible explanatory power.

In Model 5, we disregard the industry categorization and introduce our control variables that represent the market returns. In other words, Model 5 estimates the effect on 180-days log-returns from the ICO characteristics, the whitepaper dummy, and the ETH dummy after controlling for the Bitcoin log-returns and the Ethereum log-returns for the same holding period of 180-days. We observe that the ICO listing duration, the Bitcoin returns, and the Ethereum returns are significant at 5%-level and their coefficients are positive at 0.3015, 0.4834, and 0.3858, respectively. The positive coefficient of the ICO listing duration indicates that the estimated returns after 180-days increased by 30.15 percentage points if the ICOs were listed after a week. Moreover, the coefficient for Bitcoin returns and Ethereum returns clearly indicates the positive and significant influence of Bitcoin and Ethereum on 180-days token returns. The adjusted R-squared of Model 5 is 0.1404, which can be perceived as a reasonable fit where the independent variables have some explanatory power.

Model 6 includes one additional control variable to Model 5. In Model 6, we introduce the pandemic dummy as the additional control variable. This regression model intends to test the effect of the pandemic on the ICO 180-days HPRs. We see that the pandemic control variable is significant at 1% -level and strongly indicates that the pandemic period impacts 180-day post-ICO returns. The coefficient is negative at -0.5918, implying that ICOs that were listed and traded before the pandemic have 59.18 percentage points lower estimated 180-days returns than the ICOs that were listed and traded after the pandemic. In addition, the clear influence of Bitcoin on the token return is still substantiated while the influence of Ethereum is no more significant. The adjusted R-squared of Model 6 is 0.1551, which indicates that some variations in 180-days log-returns are explained by the included variables and that the goodness of fit is at an acceptable level, slightly above Model 5.

Finally, Model 7 is our unrestricted model estimated in equation 4 for 180-days post-ICO log-returns. The model includes all the variables from Model 6, in addition to the binary variables that resemble the ventures' operating industry. In Model 7, except for ICO listing duration, all other ICO characteristics variables are insignificant. The positive coefficient for the ICO listing duration is 0.4116 and thus indicates that estimated returns after 180-days increase by 41.16 percentage points if the ICOs were listed after a week. Moreover, none of the industry dummies are significant. Thus, the industry in which the venture operates does not substantiate an indication of effect.

Furthermore, the pandemic control variable is still significant at 1% -level and strongly indicates that the pandemic dummy's impact on the 180-day post-ICO returns. The coefficient is negative at -0.5761, slightly less than Model 6, implying that the ICOs that were listed and traded before the pandemic have 57.61 percentage points lower estimated 180-days returns than the ICOs that were listed and traded after the pandemic. In addition, the clear influence of Bitcoin on the token returns is still substantiated while the influence of Ethereum was no more significant, like Model 6. The adjusted R-squared of Model 7 is 0.1463, which still indicates that some variations in the 180-days log-returns are explained by the included variables. However, it should be noted that the inclusion of industry dummies degrades the explanatory power of the independent variables shown by the marginal decrease in adjusted R-squared values.

### 6.4.4 Regression model for 365-Days holding period returns

In Table 6.9, we present the results from our longer-term regression models. Like Table 6.8, Table 6.9 also presents the estimated coefficients, the standard error (in parentheses), the number of observations, the R-squared values, and the adjusted R-squared values of all the regression models. The regression models estimated in Table 6.9 measure the effects of the independent variables on the cumulative token returns after 365 days of trading. As earlier, the models are numbered from 1 to 7 and provide the results after regressing the ICOs 365-days HPRs with different sets of the independent variables. Contrary to the models in Table 6.8, all the regression models in Table 6.9 have positive adjusted R-squared values for all fitted models which signifies that some variations in 365-days log-returns are explained by the included variables.

**Table 6.9:** Cross-sectional determinants of 365-days holding period returns

| ICO_365_HPR (log) | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| Constant | -1.4197*** | -1.0867*** | -0.5212 | -0.6178+ | -0.9378** | -0.5441 | -0.5578 |
| | -0.174 | -0.2582 | -0.3245 | -0.3614 | -0.358 | -0.3689 | -0.4122 |
| ICO Characteristics | | | | | | | |
| Log_Listing_price | -0.1018* | -0.008 | -0.0144 | -0.0119 | -0.0004 | -0.0553 | -0.0503 |
| | -0.0447 | -0.0357 | -0.0358 | -0.0363 | -0.0354 | -0.0382 | -0.0387 |
| Log_Raised Capital | -0.11891+ | -0.0676 | -0.0858+ | -0.0758 | 0.0506 | 0.0930+ | 0.0841 |
| | -0.0639 | -0.0504 | -0.0508 | -0.0516 | -0.056 | -0.0562 | -0.0574 |
| ICO_ListingDuration: More than week | 0.05033 | -0.0084 | 0.0313 | 0.0899 | 0.3622+ | 0.5156* | 0.5256* |
| | -0.2446 | -0.1943 | -0.1969 | -0.2048 | -0.1993 | -0.2002 | -0.206 |
| Whitepaper dummy | | 0.2958 | 0.2561 | 0.2429 | -0.0087 | 0.0545 | 0.0287 |
| | | -0.2725 | -0.2754 | -0.2798 | -0.2945 | -0.2889 | -0.2967 |
| ETH dummy | | | -0.6242** | -0.6504** | -0.4962* | -0.5526* | -0.5509* |
| | | | -0.2324 | -0.2334 | -0.2256 | -0.2215 | -0.2239 |
| Industry dummies | | | | | | | |
| ETM | | | | 0.6843 | | | 0.5441 |
| | | | | -0.4679 | | | -0.4285 |
| FINTECH | | | | 0.3173 | | | -0.0236 |
| | | | | -0.2465 | | | -0.2353 |
| HTS | | | | 0.0737 | | | -0.031 |
| | | | | -0.2347 | | | -0.2301 |
| MP | | | | -0.2 | | | 0.0822 |
| | | | | -0.4644 | | | -0.4693 |
| OTHERS | | | | -0.294 | | | 0.2746 |
| | | | | -0.3874 | | | -0.4008 |
| Control Variable | | | | | | | |
| BitCoin 365HPR (log) | | | | | 0.0406 | 0.257 | 0.2861 |
| | | | | | -0.2533 | -0.2559 | -0.2624 |
| Ethereum 365HPR (log) | | | | | 0.5197** | 0.2205 | 0.2194 |
| | | | | | -0.1653 | -0.1839 | -0.1883 |
| Pandemic dummy | | | | | | -1.0405*** | -1.0072** |
| | | | | | | -0.3039 | -0.3093 |
| Observations | 324 | 299 | 290 | 290 | 256 | 256 | 256 |
| R-squared | 0.02492 | 0.00934 | 0.03395 | 0.05117 | 0.2259 | 0.261 | 0.268 |
| Adjusted_R-squared | 0.01578 | 0.00413 | 0.01695 | 0.01716 | 0.2041 | 0.2371 | 0.2286 |

Significance levels: + $p < 0.10$ , * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: Values in parentheses refer to the standard error value. The chronological numbers in the column headings are regression model numbers.

Model 1 tests the impact of the ICO characteristics variables on the ICOs' 365-days HPRs. The main intention behind this regression model was to verify the assumption that the ICO characteristics influence the 365-days HPR of the ICOs. We observe that the log-listing price and the log-capital raised are significant at 5% and 10% level, respectively. The coefficient of the log-listing price is negative at -0.1018, which indicates that the estimated 365-day holding period return decreases by 10.18 percentage points if the log-listing price increases by 1 percentage points, ceteris paribus. Similarly, the 365-days holding period return of the ICO decreases by 11.89 percentage points when the log-raised capital increases by 1 percentage point, ceteris paribus. Whereas the ICO listing duration is insignificant. We also notice that the adjusted R-squared of Model 1 is positive at 0.0157 which implies that the explanatory power of the independent variables under consideration is very low.

Model 2 tests whether the availability of the whitepaper has any effect on the tokens' return after the 365-days holding period, including all the independent variables from Model 1. In Model 2, we regress the 365-days log HPRs on the log-listing price, the log-raised capital, the ICO listing duration, and the whitepaper dummy, a binary variable. We observe that this model has less adjusted R-squared values compared to Model 1 and none of the independent variables are significant. Hence, we can infer that the availability of whitepaper does not explain the variation in the 365-days logged returns.

Model 3 adds another dummy variable to Model 2. In this model, we regress the 365-days log-returns on all the variables that represent the ICO characteristics including the ETH dummy. This dummy considers the platform technology that the venture plans to implement. We notice that the ETH dummy is significant at 1% level, with a negative coefficient. This implies that the ventures that used the ERC20 platform have 23.24 percentage points lower estimated 365-days returns than the ventures that did not use the ERC20 platform. Moreover, we observe that the log-capital raised is significant at 10% level, the same as Model 1, but at a lower coefficient value of -0.0858. This coefficient of the log-raised capital indicates that the estimated 365-days holding period return decreases by 8.58 percentage points if the raised capital increases by 1 percentage points, ceteris paribus. Comparing Model 1 and Model 3, we can infer that the higher explanatory power of the raised capital variable in Model 1 was to some extent due to the platform used by the ventures. The adjusted R-squared value of Model 3 is positive at 0.016965 suggesting some explanatory power of the independent variables. However, the adjusted R-squared value is very low.

In Model 4, we introduce an additional categorical variable for industry on top of Model 3. Model 4 tests if the ventures operating in certain industries are more prone to 365-days capital gains. Unlike Model 3, the ETH dummy is the only significant variable in Model 4. The coefficient of the ETH dummy is -0.6504 suggesting that the ICO 365-days HPR for the ventures that used the ERC20 platform was 65.04 percentage points less than the ventures that did not use the ERC 20 platform. In other words, the ventures that used other platforms, not the ERC20, registered higher 365-days HPRs. The adjusted R-squared value of Model 4 is marginally better than Model 3 at 0.01716 and suggests some explanatory power of the independent variables.

In Model 5, we introduced our control variable that captures the effect of the cryptocurrency market. We combine the independent variable from Model 3 with two control variables-Bitcoin and Ethereum log 365-days holding period returns. We observe that the ICO listing duration, the ETH dummy, and Ethereum's 365-days HPRs are significant at 10%, 5%, and 1% -level, respectively. The positive coefficient for the ICO listing duration is 0.3622 and indicates that the estimated returns after 365-days holding period increases by 36.22 percentage points if the ICO were listed after a week. Whereas the coefficient of the ETH dummy is negative at -0.4962, which implies that the ventures that use the ERC20 platform have 49.62 percentage points lower estimated 365-days returns than those ventures that did not use the ERC20 platform. Moreover, the coefficient of the Ethereum 365-days HPR is 0.5197. This clearly indicates the positive and significant influence of the Ethereum price movements on the tokens' 365-days holding period returns. The adjusted R-squared value of Model 5 is 0.2041, which can be perceived as a good fit where the independent variables have some explanatory power.

In Model 6, we introduce the pandemic dummy as the additional control variable along with the existing independent variables from Model 5. With this regression model, we intend to check the effect of the pandemic on the ICOs' 365-days HPRs. We notice that the pandemic control variable is significant at 0.1% -level and strongly indicates that the pandemic period has a significant impact on the 365-days post-ICO returns.

The coefficient of the pandemic dummy is negative at -1.0405, implying that the ICOs that were listed and traded before the pandemic have 104.05 percentage points lower estimated 365-days returns than those ICOs that were listed and traded after the pandemic. Moreover, the log-raised capital is positive and significant at 10% level with a value of 0.09298. Unlike Model 1 and 3, the coefficient for the log-raised capital in the Model 6 is positive which implies that the 365-days returns for the post-Covid ICOs are estimated to be 9.29 percentage points higher for every 1 percentage points increase in the raised capital, ceteris paribus. Furthermore, the ICO listing duration and the ETH dummy are also significant at 5% level. The positive coefficient for the ICO listing duration is 0.5156 and thus indicates that the estimated returns after 365-days increase by 51.56 percentage points if the ICOs were listed after a week in the post-Covid period, ceteris paribus. Whereas the coefficient for the ETH dummy is negative at -0.5526, which implies that the ventures that operated on the ERC20 platform have 55.26 percentage points lower estimated 365-days returns than those ventures that did not use the ERC20 platform during the post-Covid period. In addition, the influence of Ethereum's return on the tokens' 365-days HPR is no more significant. The adjusted R-squared value of Model 6 is 0.2371, which indicates that some variation in the 365-days holding period returns is explained by the included explanatory variables and that the goodness of fit can be perceived as good, slightly above Model 5.

Finally, in our unrestricted model, Model 7, we estimate the effects of all the independent variables on the 365-days post-ICO log-returns. The model includes all the variables from Model 6, in addition to binary variables that resemble ventures' operating industry. In Model 7, except for the ICO listing duration, all the other ICO characteristics variables are insignificant like the model estimated for the 180-days post ICO log-returns. The coefficient for the ICO listing duration is 0.5256 (lower than the coefficient for 180-days model in Table 6.8) and thus indicates that the estimated returns after 365-days holding period increase by 52.56 percentage points if the ICO were listed after a week during the post-Covid period, ceteris paribus. Moreover, none of the industry dummies are significant which is consistent with the unrestricted model estimated in Table 6.8. Thus, we can infer that the industry in which the venture operates does not affect the longer-term returns, both 180 and 365-days HPRs.

Furthermore, the pandemic control variable is still significant at 1% -level and strongly indicates that the pandemic dummy's impact on 365-day post-ICO returns. The coefficient is negative at -1.007 implying that the ICOs' that were listed and traded before the pandemic has 100.7 percentage points lower estimated 365-days returns than those ICOs that were listed and traded after the pandemic. It is worth mentioning that the coefficient for the pandemic dummy in this unrestricted model is substantially higher compared to -0.5761 from the unrestricted model in Table 6.8. This implies that the 365-day returns were affected more compared to the 180-days return between the pre-Covid and the post-Covid periods. In addition, the ICO listing duration and the ETH dummy have a clear influence on the ICOs 365-days holding period return, as both these variables are significant at 5% level.

Moreover, none of the crypto-market variables, namely, the Bitcoin return and the Ethereum returns are significant in explaining the 365-days post-ICO returns. Although the Bitcoin return was found significant in explaining the 180-days post-ICO returns in the unrestricted model presented in Table 6.8, similar significance was not evident for the 365-days HPRs. The adjusted R-squared value of model 7 is 0.2286, which still indicates that some variations in the 365-days HPRs are explained by the included explanatory variables. However, it should be noted that the inclusion of the industry dummy degrades the explanatory power of the independent variables represented by a slight decrease in the adjusted R-squared values.

### 6.4.5 Discussion of cross-sectional effects on the longer-term HPRs

Contrasting the two unrestricted models in Table 6.8 and Table 6.9, we can see that the ICO listing duration is the only independent variable, out of 5 ICO characteristics variables, that has a statistically significant effect on both the 180-days and 365-days HPRs. In our unrestricted model for 180-day HPRs, the ICO listing duration has a positive coefficient of (0.4116) and a significant impact at 1%-level. Whereas, the ICO listing duration has a positive coefficient (0.5256) and a significant impact at 5%-level for the 365-days HPRs. This indicates that the investors' 365-days HPRs are more positive if the ICO listing duration is more than a week relative to their 180-days HPR. First, we can argue that longer listing duration facilitates proper screening of the ICOs by the exchanges which may indicate better trust in the ventures. Further, the longer-listing duration reduces the liquidity benefits of the ICOs which might cause the ICO listing price to be substantially low, which consequently allows the secondary investors to buy such ICOs at lower prices and thus, increases their 365-days holding period returns. On the contrary, although we have not incorporated the operational status of the project financed by the ICOs, we may assume that longer holding period allows the investors and the market to observe the actual operation of the project financed by the ICOs which is hence represented by higher long-terms returns for the secondary investors.

Moreover, we also see that the ETH dummy has a significant and negative effect on 365-day HPRs of the ICOs after controlling for the pandemic dummy. From this, we can infer that the ERC20 platform has negative effects on the 365-days HPR, especially for the ICOs that were listed and traded after the pandemic. One possible explanation for such negative affect can be drawn from the increased popularity of new platform technologies like SOLONA and NEO. Moreover, this can also indicate the increased technical affluence of the ventures technical team to introduce a better and reliable technological platform tailor-made for its project development and execution.

Further, we found that the ventures operating in certain industries evidently do not affect the longer-term ICOs returns. As mentioned before, we can again argue that the firm-specific product or services are of more interest to the investors but not the industries. Thus, this broader blockchain based technology sector might have higher implications during the pre-Covid and the post-Covid period than the sub-categories that fall within it. Therefore, based on our findings we cannot establish any significant effect of the industry category dummy on the 180-days and 365-days HPRs.

Furthermore, we found that the cryptocurrency market returns have no significant effect on the 365-days HPRs of the ICOs. Whereas, the pandemic dummy has a negative and significant effect on the 365-day HPRs of the ICOs. This may indicate that longer-terms investors hold these ICOs for the value created by the ventures rather than for their speculative benefits. Like IPOs, if the venture performs well the long-term investors are benefited irrespective of the market movements. We can also, intuitively, argue that the ICOs issued recently are not issued against Bitcoin, like before. Moreover, Katiampa et al.

(2022) found that altcoins became significantly more popular during the Covid-19 crisis. Thus, these recent ICOs are more immune from the price movements in Bitcoins as they fall under the broader category of altcoins. Since new ICOs are not built on the ERC20 platform we are not surprised by the insignificant relationship between the Ethereum market return and 365-days ICO HPRs.

Finally, based on our findings we can infer that the ICOs that ended before March 11, 2020, registered lower longer-terms HPRs compared to the ICOs that ended after March 11, 2020. One of the possible explantion for this could be inferred from the previous studies of Benedetti and Kostovetsky (2021), and Fisch (2019) wherein they argued that the ICO market was at boom during 2017 with a huge amount of the ICO capital raised. Our data set includes ICO after 2018 when the market can be assumed to be at its saturation. Hence, we can conclude that the ICOs listed from 2018 to early 2020 registered lower longer-term returns. However, the ICOs that were listed after March 2020 registered higher longer-term returns. We argue that the possible reasons for such higher post-Covid longer-term returns may be due to the dramatic increase in crypto users since 2020 (Feyen et al., 2022). Moreover, Dittmar and Wu (2019) found out that the ICO cryptocurrencies significantly outperformed the non-ICO cryptocurrencies, during the cryptocurrency market crash in 2018. This may indicate that the ICO cryptocurrencies act more independently than the non-ICOs and show better market performance which is why the ICOs' longer-term returns may be better during the post-Covid period, irrespective of higher market volatility.

# 7 Conclusion

In this section, we summarize our research and our findings from previous analysis. We then provide limitations experienced in this work before finally recommending relevant topics for future research.

## 7.1 Summary

In our study, we have looked at the performance of ICOs by analyzing the possible impact of the funding predictors, the raised capital and the industry categories on the initial and the longer-terms returns of the ICOs before and during the pandemic. The purpose of this study was to answer the following research question:

> "How do the funding predictors, the raised capital and the industry category affect the ICOs' initial and longer-term returns before and during the COVID-19 pandemic?"

To answer this question, we collected data from several sources containing detailed information on the ICO funding predictors, as well as the historical token price movements post-ICO. We gathered information on ICO characteristics, raised capital, industry categories, cryptocurrency market movement represented by Bitcoin and Ethereum segregated for the pandemic periods. We used these variables to estimate a multivariate regression model to examine how the different variables may contribute to the ICOs' initial returns.

We address the impact of the same variables on the longer-term holding period returns to evaluate if the effect varied whether ICOs were purchased after listing. We have focused on 180-days and 365-days returns after listing, but we have also briefly looked at the returns after 1-day, 7-days, 30-days and 90-days. We intended to test whether these variables still had some effect on the 180-days and 365-days holding period returns for two periods, the pre-Covid and the post-Covid. We analyzed this data using a multivariate regression model to see the magnitude and the significance of these variables on 180-days and 365-days holding period returns after listing, for both the pre-Covid and post-Covid samples.

Our findings in the first analysis indicates that the ICO price, out of 5 ICO characteristics variables/funding predictors, has some effect on the initial returns of ICOs. This is coherent with our assumptions that we derived from past studies. However, our assumption regarding the influence of the ICO raised capital and the ICO duration on the initial returns did not hold when we considered for the pandemic periods. In addition, what industry a venture operates in does not seem to matter in terms of their initial returns irrespective of the period such ICOs were listed and traded. This finding contradicts with our assumption. This can be explained by the fact that investors may not be industry specific and that broader blockchain industry category might have higher implications during the pre-Covid and the post-Covid periods.

The cryptocurrency market returns and the pandemic has had significant effect on ICO initial returns. Hence, we conclude that ICOs listed during 2018 to early 2020 registered lower initial returns compared to the ICOs listed after March, 2020. One possible reasons for such higher post-Covid initial return may be due to the degrading capital markets and increased hype around cryptocurrencies. However, as the economic situation improves and the captial market regains its momentum such higher initial returns on ICO investment may not continue.

Our second analysis indicates that the longer ICO listing duration has positive effect on the longer-term holding period returns. Such higher returns may arise due to increased trust on venture performance as longer holding period allows the investors and the market to observe the actual operation of the project financed by the ICOs. Moreover, the longer-listing duration reduces the liquidity benefits of the ICOs which might cause the ICO listing price to be substantially low, which consequently allows the secondary investors to buy such ICOs at lower prices and thus, increases their longer-term holding period returns. We also see that the ETH platform has a significant and negative effect on 365-day HPRs of the ICOs after controlling for the pandemic dummy. This may be explained by the increased popularity of new platform like SOLONA and NEO. Moreover, this can also indicates the increased technical capability of the ventures and their reliability in executing the project.

Further, what industry yields higher longer-term ICOs returns is not clear, and we have no specific reason to suggest any industry-specific variations. This is contradictory to what we found in the literature where high-tech service industry had some significant impact on the ICOs intitial returns which we assumed to continue for the longer-terms returns as well. Therefore, we may conclude that the investors should invest based on the product of the ventures, rather than what industries may be profitable.

When considering the cryptocurrency market returns, investors longer terms return are less likely to be driven by the price movements of Bitcoin or Ethereum. This may indicate that longer-terms investors hold these ICOs for the value created by the ventures rather than for their speculative benefits. Moreover, increased popularity of altcoins mainly during the Covid-19 crisis have made these recent ICOs more immune from the price movements in Bitcoins which may be another explanation for why ICOs longer-term performance are unaffected by the general movement in Bitcoin and Ethereum prices.

Finally, based on our findings we can infer that the ICOs that ended before March 11, 2020, registered lower longer-terms HPRs compared to the ICOs that ended after March 11, 2020. We may associate that with the saturated status of overall cryptocurrency market during 2018. However, the ICOs that were listed after March 2020 registered higher longer-term returns. This is mainly due to the dramatic increase in crypto users since 2020. Moreover, we may reason that the ICO cryptocurrencies act more independently than the non-ICOs and hence performed better during the post-Covid period, irrespective of higher market volatility.

## 7.2 Limitations

A major limitation of our study is the sample size. Although we have collected data points for more than 900 observations, our analysis was performed on relatively fewer observations which varied for initial returns and longer-terms return analysis. We are aware of more than 5000 ICOs that are active and traded, while our sample size only represents a small fraction. Such a small sample size limits the generalization of the findings. By potentially increasing the sample size the sample would be more likely to represent the population and the probability of generalizing the inference would increase. Moreover, our sample is also exposed to survivorship bias like other past studies conducted in this topic.

The unavailability of one reliable database on ICOs compelled us to manually collect the data for this study. Furthermore, the time limit restricted us to from collecting data from other aggregator website which resulted for such smaller dataset.

Moreover, one of the analysis performed in this work concerns with the effect of funding predictors on longer-terms holding period returns. Since, we have selected the time horizon to capture the pre-Covid and the post-Covid effects on returns we have limited the holding period to maximum of 365-days as most of the observation were relatively recents. Finally, since ICOs are very new topic to us we neither have access nor have the technical expertise to evaluate the content of some technical variable such as the whitepaper and the ETH dummy; thus, we considered only their availability while performing the analysis.

## 7.3 Avenues for further study

After observing all the findings in our study, we see that their exist several interesting avenues to explore in future studies. First, we only consider some of the funding predictors in our analysis while we have not covered other funding predictors like source code, ratings, venture's technical team which may have some affect on the returns. It will be interesting to see how such additional funding predictors influence the ICO performance.

Second, we have collected limited number of observations for our study which could limit the accuracy and generalization of our finding. We strongly believe that a larger data set would provide more reliable depth in validating our findings, which could be another extension to this work.

Third, in our discussion we highlighted that the pre-Covid period considered in this thesis is a period where the cryptomarket had saturated. Such saturated nature of the market might have some effects on our findings. Thus, it would be worth including the older ICOs from different periods to examine the consistency and the relevance of our finding at different times.

Finally, we strongly believe that the size of ICO token and their market capitalization also effect their initial and longer-terms performances which is not considered in our study. Hence, a value-weighted measure for returns, as a dependent variable, can be used in further studies to compare the performance of ICOs which may provide contrasting finding than this study.

# References


Abel, A., Bernanke, B., and Croushore, D. (2017). *Macroeconomics*. Pearson UK.

Acheson, N. (2021). Crypto long short: No, bitcoin was not a response to the financial crisis.

Adhami, S., Giudici, G., and Martinazzi, S. (2018). Why do businesses go crypto? an empirical analysis of initial coin offerings. *Journal of Economics and Business*, 100:64–75.

Anglin, A. H., Short, J. C., Drover, W., Stevenson, R. M., McKenny, A. F., and Allison, T. H. (2018). The power of positivity? the influence of positive psychological capital language on crowdfunding performance. *Journal of Business Venturing*, 33(4):470–492.

Bardinelli, J. and Frumkin, D. (2018). Cryptocurrencies in the top 100 with working products that are in-use.

Benedetti, H. and Kostovetsky, L. (2021). Digital tulips? returns to investors in initial coin offerings. *Journal of Corporate Finance*, 66:101786.

Birru, J. and Wang, B. (2016). Nominal price illusion. *Journal of Financial Economics*, 119(3):578–598.

Boreiko, D. and Sahdev, N. K. (2018). To ico or not to ico–empirical analysis of initial coin offerings and token sales. *Available at SSRN 3209180*.

Catalini, C. and Gans, J. S. (2018). Initial coin offerings and the value of crypto tokens. Technical report, National Bureau of Economic Research.

Ciaian, P., Rajcaniova, M., et al. (2018). Virtual relationships: Short-and long-run evidence from bitcoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, 52:173–195.

Coinmarketcap (2022). Global cryptocurrency market charts.

Crain, N., Parrino, R., and Srinivasan, R. (2017). Uncertainty, prospectus content, and the pricing of initial public offerings. *Available at SSRN 3082429*.

da Silva, P. P. (2019). Corporate governance, earnings quality and idiosyncratic crash risk during the 2007–2008 financial crisis. *Journal of Multinational Financial Management*, 51:61–79.

Dittmar, R. F. and Wu, D. A. (2019). Initial coin offerings hyped and dehyped: An empirical examination. *Available at SSRN 3259182*.

Feyen, E., Kawashima, Y., and Mittal, R. (2022). Crypto-assets activity around the world: Evolution and macro-financial drivers. *Washington, DC: World Bank*.

Fisch, C. (2019). Initial coin offerings (icos) to finance new ventures. *Journal of Business Venturing*, 34(1):1–22.

Fisch, C., Masiak, C., Vismara, S., and Block, J. H. (2018). Motives to invest in initial coin offerings (icos). *Available at SSRN 3287046*.

Fisch, C. and Momtaz, P. P. (2020). Institutional investors and post-ico performance: an empirical analysis of investor returns in initial coin offerings (icos). *Journal of Corporate Finance*, 64:101679.

Howarth, J. (2022). How many cryptocurrencies are there in 2022?

Hsieh, H.-C. and Oppermann, J. (2021). Initial coin offerings and their initial returns. *Asia Pacific Management Review*, 26(1):1–10.

Huang, J. (2022). How does the covid-19 impact the cryptocurrency? In *2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)*, pages 900–908. Atlantis Press.

Hutcheson, G. D. and Moutinho, L. A. M. (2011). The sage dictionary of quantitative management research. *The SAGE Dictionary of Quantitative Management Research*, pages 1–344.

ICObench (2022). Stats and facts.

International Institute of Finance, I. (2018). Initial coin offerings: the frontier of financing.

Jalan, A., Matkovskyy, R., and Yarovaya, L. (2021). "shiny" crypto assets: A systemic look at gold-backed cryptocurrencies during the covid-19 pandemic. *International Review of Financial Analysis*, 78:101958.

Jana, R. K. and Das, D. (2020). Did bitcoin act as an antidote to the chinese equity market and booster to altcoins during the novel coronavirus outbreak? *Available at SSRN 3544794*.

Katsiampa, P., Yarovaya, L., and Zięba, D. (2022). High-frequency connectedness between bitcoin and other top-traded crypto assets during the covid-19 crisis. *Journal of International Financial Markets, Institutions and Money*, page 101578.

Kher, R., Terjesen, S., and Liu, C. (2021). Blockchain, bitcoin, and icos: a review and research agenda. *Small Business Economics*, 56(4):1699–1720.

Link, N. D. (2022). Bitcoin number of transactions.

Martino, P., Wang, K. J., Bellavitis, C., and DaSilva, C. M. (2020). An introduction to blockchain, cryptocurrency and initial coin offerings. In *New frontiers in entrepreneurial finance research*, pages 181–206. World Scientific.

Masiak, C., Block, J. H., Masiak, T., Neuenkirch, M., and Pielen, K. N. (2020). Initial coin offerings (icos): market cycles and relationship with bitcoin and ether. *Small Business Economics*, 55(4):1113–1130.

Mnif, E., Jarboui, A., and Mouakhar, K. (2020). How the cryptocurrency market has performed during covid 19? a multifractal analysis. *Finance research letters*, 36:101647.

Momtaz, P. (2021). Data: Paulmomtaz.

Moore, S. (2021). History of covid-19.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, page 21260.

Noogin (2018). The financial crisis and history of bitcoin.

Pereira da Silva, P. (2007). Corporate governance, earnings quality and idiosyncratic crash risk during the 2007-2008 financial crisis. *Earnings Quality and Idiosyncratic Crash Risk During the*, 2008.

R Core Team (2017). *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria.

Ritter, J. R. and Welch, I. (2002). A review of ipo activity, pricing, and allocations. *The journal of Finance*, 57(4):1795–1828.

Saleemi, J. (2021). Crypto market and liquidity risk in environments due to pandemic uncertainty. *Journal of Contemporary Research in Business, Economics and Finance*, 3(4):168–178.

Szmigiera, M. (2022). Impact of the coronavirus pandemic on the global economy - statistics facts.

Tobias, A. (2021). The future of finance and the global economy: Facing global forces, shaping global solutions.

Wooldridge, J. M. (2020). Introductory econometrics 7th ed.

Zetzsche, D. A., Buckley, R. P., Arner, D. W., and Föhr, L. (2017). The ico gold rush: It's a scam, it's a bubble, it's a super challenge for regulators. *University of Luxembourg Law Working Paper*, (11):17–83.

# Appendix

## A1 Dataset

### Table A1.1: 20 observations of total observations

| n | Symbol | Name | Listed/ Notlisted | ICO_start | ICO_end | ICO_price | Listing_date | Current_price | Listing_price_Open | Listing_price_Close |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | WRX | WazirX | 1 | 27-Jan-20 | 04-Feb-20 | $0.020 | 07-Feb-20 | $0.681 | $0.121 | $0.114 |
| 2 | PNK | Kleros | 1 | 10-Jan-20 | 10-Feb-20 | $0.068 | 02-Nov-18 | $0.097 | $0.007 | $0.008 |
| 3 | HDAO | HyperDAO | 1 | 24-Feb-20 | 24-Feb-20 | $0.010 | 13-Mar-20 | $0.016 | $0.022 | $0.023 |
| 4 | BDK | Bidesk | 0 | 27-Feb-20 | 28-Feb-20 | $0.080 | NA | | | |
| 5 | XX | Elixxir | 0 | 22-Jan-20 | 20-Mar-20 | $0.360 | NA | | | |
| 6 | SOL | Solana | 1 | 16-Mar-20 | 24-Mar-20 | $0.220 | 11-Apr-20 | $134.430 | $0.951 | $0.777 |
| 7 | KPAD | KickPad | 1 | 01-Mar-20 | 26-Mar-20 | $0.040 | 27-Mar-21 | $0.004 | $2.050 | $3.090 |
| 8 | KAI | KardiaChain | 1 | 07-Apr-20 | 07-Apr-20 | $0.001 | 18-Apr-20 | $0.050 | $0.001 | $0.001 |
| 9 | DEP | DEAPcoin | 1 | 07-Apr-20 | 07-Apr-20 | $0.003 | 11-Apr-20 | $0.031 | $0.006 | $0.005 |
| 10 | CTSI | Cartesi | 1 | 20-Apr-20 | 21-Apr-20 | $0.015 | 24-Apr-20 | $0.501 | $0.057 | $0.053 |
| 11 | STAKE | STAKE | 1 | 27-Apr-20 | 28-Apr-20 | $0.550 | 20-May-20 | $14.110 | $1.630 | $1.730 |
| 12 | UMA | UMA | 1 | 29-Apr-20 | 29-Apr-20 | $0.250 | 26-May-20 | $7.970 | $1.350 | $1.210 |
| 13 | RVX | Rivex | 1 | 29-Apr-20 | 30-Apr-20 | $0.035 | 12-May-20 | $0.004 | $0.081 | $0.083 |
| 14 | MLK | Mil.I | 1 | NA | 30-Apr-20 | $0.125 | 06-Aug-20 | $1.000 | $0.210 | $0.207 |
| 15 | JST | JUST | 1 | 05-May-20 | 05-May-20 | $0.002 | 08-May-20 | $0.086 | $0.008 | $0.006 |
| 16 | 2KEY | 2Key | 1 | 02-May-20 | 10-May-20 | $0.045 | 15-May-20 | $0.006 | $0.094 | $0.050 |
| 17 | CELO | Celo | 1 | 10-May-20 | 11-May-20 | $1.000 | 23-May-20 | $3.400 | $0.833 | $2.500 |
| 18 | FNX | FinNexus | 1 | 09-May-20 | 16-May-20 | $0.100 | 19-Jun-20 | $0.000 | $0.086 | $0.085 |
| 19 | NDN | NDN Link | 1 | 19-May-20 | 19-May-20 | $0.006 | 26-May-20 | $0.003 | $0.017 | $0.017 |
| 20 | TON | Tokamak Network | 1 | NA | 31-May-20 | $0.450 | 30-Aug-20 | $5.100 | $6.930 | $6.930 |

Note: Table A1.1, A1.2 and A1.3 are taken from our dataset. Only 20 observations are listed on this section. ICO dates can be seen above, along with some price information

### Table A1.2: Additional variables 1

| n | Symbol | Name | After_1_Day | After_7_Days | After_14_Days | After_30_Days | After_90_Days | After_180_Days | After_365_Days |
|---|---|---|---|---|---|---|---|---|---|
| 1 | WRX | WazirX | $0.094 | $0.111 | $0.084 | $0.202 | $0.138 | $0.129 | $0.120 |
| 2 | PNK | Kleros | $0.008 | $0.008 | $0.007 | $0.005 | $0.005 | $0.008 | $0.009 |
| 3 | HDAO | HyperDAO | $0.022 | $0.027 | $0.030 | $0.034 | $0.022 | $0.019 | $0.010 |
| 4 | BDK | Bidesk | | | | | | | |
| 5 | XX | Elixxir | | | | | | | |
| 6 | SOL | Solana | $0.662 | $0.681 | $0.643 | $0.537 | $1.020 | $2.370 | $27.930 |
| 7 | KPAD | KickPad | $2.920 | $3.800 | $2.880 | $0.899 | $0.022 | $0.013 | $0.004 |
| 8 | KAI | KardiaChain | $0.001 | $0.001 | $0.001 | $0.001 | $0.012 | $0.017 | $0.115 |
| 9 | DEP | DEAPcoin | $0.006 | $0.005 | $0.005 | $0.005 | $0.009 | $0.005 | $0.010 |
| 10 | CTSI | Cartesi | $0.042 | $0.040 | $0.032 | $0.033 | $0.053 | $0.032 | $0.442 |
| 11 | STAKE | STAKE | $1.830 | $1.500 | $1.630 | $1.750 | $8.050 | $8.130 | $12.540 |
| 12 | UMA | UMA | $1.380 | $1.420 | $1.600 | $2.030 | $6.940 | $8.170 | $15.750 |
| 13 | RVX | Rivex | $0.093 | $0.074 | $0.063 | $0.058 | $0.115 | $0.136 | $0.069 |
| 14 | MLK | Mil.I | $0.205 | $0.228 | $0.218 | $0.186 | $0.155 | $0.144 | $1.120 |
| 15 | JST | JUST | $0.007 | $0.008 | $0.008 | $0.008 | $0.051 | $0.018 | $0.137 |
| 16 | 2KEY | 2Key | $0.041 | $0.102 | $0.130 | $0.053 | $0.153 | $0.023 | $0.051 |
| 17 | CELO | Celo | $1.520 | $1.500 | $1.610 | $1.810 | $2.390 | $1.680 | $2.660 |
| 18 | FNX | FinNexus | $0.085 | $0.086 | $0.084 | $0.099 | $0.216 | $0.129 | $0.017 |
| 19 | NDN | NDN Link | $0.017 | $0.017 | $0.015 | $0.012 | $0.009 | $0.004 | $0.004 |
| 20 | TON | Tokamak Network | $6.280 | $4.960 | $5.240 | $3.850 | $2.440 | $6.370 | $8.550 |

Note: Table A1.1, A1.2 and A1.3 are taken from our dataset. Only 20 observations are listed on this section. ICO price information for 20 currencies after given number of days

**Table A1.3:** Additional variables 2

| n | Symbol | Name | Interest | Category | Received | Goal | Type | White-paper | Total Tokens |
|---|---|---|---|---|---|---|---|---|---|
| 1 | WRX | WazirX | NR | Exchange | $2,000,000.00 | $2,000,000.00 | BEP2 | 1 | 1,000,000,000 |
| 2 | PNK | Kleros | NR | Blockchain Service | $3,756,853.00 | $5,960,000.00 | ERC20 | 1 | 1,000,000,000 |
| 3 | HDAO | HyperDAO | NR | Finance | $2,000,000.00 | $2,000,000.00 | ERC20 | 0 | 5,000,000,000 |
| 4 | BDK | Bidesk | NR | Exchange | $240,000.00 | $240,000.00 | ERC20 | 1 | 100,000,000 |
| 5 | XX | Elixxir | WL | Blockchain Service | $17,700,000.00 | $23,000,000.00 | ERC1404 | 1 | 1,000,000,000 |
| 6 | SOL | Solana | NR | Blockchain Service | $25,660,000.00 | $29,280,000.00 | ERC20 | 1 | 500,000,000 |
| 7 | KPAD | KickPad | NR | Platform | $- | $- | ERC20 | 1 | 203,768,315 |
| 8 | KAI | KardiaChain | NR | Blockchain Service | $4,280,000.00 | $4,280,000.00 | ERC20 | 1 | 5,000,000,000 |
| 9 | DEP | DEAPcoin | NR | Blockchain Platform | $20,000,000.00 | $20,000,000.00 | ERC20 | 1 | 30,000,000,000 |
| 10 | CTSI | Cartesi | HIGH | DAPP | $1,500,000.00 | $1,500,000.00 | ERC20 | 1 | 1,000,000,000 |
| 11 | STAKE | STAKE | HIGH | Blockchain Service | $- | $220,000.00 | ERC20 | 1 | 8,537,500 |
| 12 | UMA | UMA | MEDIUM | Smart Contract | $- | $5,200,009.00 | ERC20 | 0 | 100,000,000 |
| 13 | RVX | Rivex | NR | Blockchain Platform | $- | $- | WRC20 | 1 | NA |
| 14 | MLK | Mil.I | NR | Blockchain Service | $- | $- | ERC20 | 1 | NA |
| 15 | JST | JUST | HIGH | Stable Coin | $4,066,920.00 | $4,070,000.00 | ERC20 | 1 | 9,900,000,000 |
| 16 | 2KEY | 2Key | NR | Blockchain Service | $600,000.00 | $1,400,000.00 | ERC20 | 1 | 600,000,000 |
| 17 | CELO | Celo | MEDIUM | Payment | $6,500,000.00 | $1,248,000,000.00 | ERC20 | 1 | NA |
| 18 | FNX | FinNexus | NR | Finance | $4,400,000.00 | $4,400,000.00 | ERC20 | 1 | 500,000,000 |
| 19 | NDN | NDN Link | NR | Blockchain Service | $2,000,000.00 | $2,000,000.00 | ERC20 | 1 | 5,000,000,000 |
| 20 | TON | Tokamak Network | NR | Platform | $388,500.00 | $- | ERC20 | 1 | NA |

Note: Table A1.1, A1.2 and A1.3 are taken from our dataset. Only 20 observations are listed on this section.
ICO project information, category and rating.