THE INFLUENCE OF INSTITUTIONAL INVESTORS ON INITIAL COIN OFFERING PERFORMANCE

REBECKA MOFORS

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Abstract

The popularity of raising capital through Initial Coin Offerings and the rapidly evolving cryptocurrency market calls for a deeper understanding of success factors that can predict ICO success. In this paper, we examine the influence of institutional investors on ICO success by measuring the token's Buy and Hold Abnormal Returns and the venture's operational progress 180 days after the first day of trading. We find that institutional investor backed ventures outperform non-investor backed in terms of both investor returns, post-ICO employment and employment growth. Institutional investor backing can also help mitigate the information asymmetries in the ICO market through value signaling. In the unstable surroundings of the cryptocurrency market our results indicate that measuring the ICO performance with tangible measurements is preferable to measurements based on token prices.

Keywords

Initial coin offering, entrepreneurial finance, crowdfunding, blockchain, cryptocurrencies, institutional investors

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1 Introduction

The cryptocurrency market has experienced strong growth throughout the years (Liu et al., 2022). In this market, companies can raise capital by issuing and selling cryptographically secure digital assets, commonly referred to as tokens (Howell et al., 2020). This blockchain established crowdfunding method, called Initial Coin Offerings (ICOs), enables inexpensive financing for all types of ventures without a financial intermediary (Momtaz, 2020; Howell et al., 2020; Liu et al., 2022; Lee & Parlour, 2022). Due to its low costs and great liquidity this fundraising mechanism has vast potential for the future (Yermack, 2017; Howell et al., 2020; Fisch & Momtaz, 2020).

The first ICO was issued in 2013, and the method grew explosively between 2017 and 2018 (Fisch, 2019). During this period, numerous scammer-issued tokens were concealed frauds (Hornuf & Schwienbacher, 2021). As token buyers lack legal protection due to the absence of regulation, signalling value and certification is of importance for ICO success (Zhang et al., 2018). Despite the decreased number of ICOs issued today, the market is evolving, and this form of fundraising is still a powerful tool for early-stage ventures.

The popularity of raising capital through ICOs and the rapidly evolving cryptocurrency market calls for a deeper understanding of success factors that predict ICO performance (Fisch & Momtaz, 2020; Howell et al., 2020). Fisch & Momtaz (2020) confirm that institutional investor (e.g., venture capital and hedge fonds) backed ICO ventures outperform non-investor-backed ventures, evaluated with the ventures' Buy and Hold Abnormal Return (BHAR). Being institutional investor backed therefore contributes to the value signalling of credibility.

Howell et al. (2020) also confirm that access to venture capital equity is important for ICO success, evaluated by enterprise growth in future employment. Fisch & Momtaz's (2020) and Howell et al.'s (2020) results align with conclusions in previous literature conducted in more traditional funding settings (see e.g. Brav & Gompers, 1997; Lewis, 2011). Although ICO performance has been studied, there is still ambiguity regarding predicting the success of the ventures that issue and sell tokens (Campino et al., 2022).

To clarify this ambiguity, this paper examines the impact of institutional investors on ICO performance, replicating Fisch & Momtaz's (2020) econometrical methodology in a cross-sectional with Howell et al.'s (2020) ICO operational progress measurements. This article's contribution is threefold. Firstly, we contribute to the literature on entrepreneurial finance, ICO signalling, and ICO performance by assessing the relationship between institutional investors and ICO success by evaluating the performance with the BHAR, employment during the ICO, post-ICO employment, and employment growth. This allows us to assess the influence of institutional investor backing on ICO success from a tangible and intangible perspective, extending Fisch & Momtaz's (2020) research from one to two viewpoints. Primarily, we create a data sample of 853 ICOs with eleven (11) control variables regarding issuer characteristics and human capital characteristics. Including these control variables in our research enable us to identify other relevant driver of ICO success.

Second, we extend Fisch & Momtaz's (2020) and Howell et al.'s (2020) research using a data sample of ICOs issued during a broader timeframe. Extending their analysis provides robustness of their research while also accounting for the evolution of the ICO industry over the years. We use data on ICOs conducted between 2014-20, while Fisch & Momtaz (2020) use a data sample of ICOs between 2015-18, and Howell et al. (2020) use a sample between 2018-19. Since the ICO market is significantly volatile (Drobetz et al., 2019; Fisch & Momtaz, 2020; Liu et al., 2022), predicting ICO success calls for measurements that take the volatility and rapid market changes into account.

Third, we contribute to future research within the ICO literature by publishing our hand-collected data sample and our python code for collecting and calculating the BHAR on GitHub.

Our results confirm the findings of Fisch & Momtaz (2020) and Howell et al. (2020) that institutional investors have a positive impact on post-ICO success. In addition, our results indicates that a selection effect exists in our sample indicating that institutional investors have a superior ability to target high-quality ventures. Moreover, we find that a platform-based business model and a pre-sale are additional factors that indicates to be of importance to ICO success. Surprisingly, we also find that institutional investors have a more substantial impact on post-ICO performance when conducting the research on a data sample with a broader timeframe than Fisch & Momtaz (2020).

We find indications that access to institutional investor capital is an essential factor to account for when predicting ICO performance. Furthermore, our results indicate that ICO elements affect ICO performance measurements differently depending on what aspect of success one focuses on. We conclude that the BHAR may not be an ideal measurement of ICO success, since the high volatility in the cryptocurrency market and that the ICO prices are argued to be influenced by fraudulent trading activities (Corbet et al., 2018; Howell et al., 2020; Fisch & Momtaz, 2020; Lee & Parlour, 2022). Instead, we conclude that more tangible measurements such as post-ICO employment and employment growth may be more favourable when predicting ICO success due to their ability to better account for traditionally established success factors such as market establishment, value creation, and operational progress (Bruderl & Preisendorfer, 1998; Reid & Smith, 2000; Howell et al., 2020).

Our findings are valuable for several reasons. The ICO market is highly impacted by investor speculations rather than robust market fundamentals (Zetzsche et al., 2018; Lee & Parlour, 2022) and has limited regulations. Therefore, it is important to understand the factors driving ICO success to mitigate fraudulent tokens (Zetzsche et al., 2018; Delivorias, 2021) This understanding is fundamental in today's economic environment, in which the interest in cryptocurrency assets is increasing (Chuffart, 2022). The ability to distinguish potential successful ICOs from those ICOs channelling money to recipients for their personal uses is especially important for retail ICO investors that do not have access to superior screening material. Our insights are also beneficial for future ICO issuers and their stakeholders to successfully launch an ICO.

In our paper, we conduct a two-stage-least square (2SLS) regression combined with a restricted control function (rCF) approach to account for the potential endogeneity in our data sample. First, we run a logistic regression to estimate the institutional investor variable by a vector of all the control variables. Second, we model the generalized residual described in section 4. Third, we conduct the 2SLS with the estimated institutional investor variable and the generalized residual included as a single control variable.

This paper is organized as follows. Section two describes our contribution to the ICO literature. Section three describes our data sample. Section four builds the econometrical models. Section five analyses the results for ICO performance. Finally, section six concludes.

2 Literature Review

Several researchers concludes that post-ICO performance is positively affected by being advised or backed by institutional investors (see e.g. Howell et al., 2020; Fisch & Momtaz, 2020; Giudici et al., 2020; Boreiko & Risteski., 2020). Fisch & Momtaz (2020) exploit a 2SLS model with a restricted control function (rCF) approach to investigate the relationship between institutional investor backing and ICO success. They evaluate the post-ICO performance with the market weighted BHAR on a sample of 565 ICOs issued between 2015-18. They find that institutional investor backed ICOs have a significantly higher post-ICO performance than non-investor backed ventures. Moreover, Fisch & Momtaz (2020) conclude that their results indicate that institutional investors can overcome information asymmetries in the ICO market by obtaining informational rents due to superior screening and coaching skills. This conclusion aligns with previous papers on traditional funding methods (see e.g., Chemmanur et al., 2011; Guo & Jiang, 2013; Sørensen, 2007). We extend Fisch & Momtaz (2020) analysis in three dimensions. First, we extend their research on a data sample of 853 ICOs issued between 2014-20. In this extension we exploit the same econometric methodology to account for potential endogeneity regarding institutional investors. Second, we conduct a cross-sectional with Howell et al.,'s (2020) paper to investigate the link between institutional investors and ICO operational progress measured by the employment during the ICO, post-ICO employment, and employment growth. This allows us to compare Fisch & Momtaz's (2020) success measurements with more tangible perspectives of ICO success. Third, we develop Fisch & Momtaz's (2020) analysis by constructing a set of control variables consisting of only significant variables from their paper, while also adding several variables regarding founder characteristics and team gender diversity used by Howell et al. (2020).

Prior studies have found a positive relationship between venture success and human capital (Unger et al., 2011; Howell et al., 2020). Human capital is generally related to experience, education, knowledge, and skills when referred to in an entrepreneurial success context (Ahlers et al., 2015). The main tests conducted by Howell et al. (2020) investigates the link between operational ICO progress and various ICO- and human capital characteristics. They measure the operational progress in these tests with the employment growth rate, ICO failure rate and exchange listings between November 2018 until July 2019 on a data sample of 961 ICOs. Like Fisch & Momtaz (2020) they find that access to token liquidity and venture capital equity is correlated with higher post-ICO employment growth. This paper differs from Howell et al. (2020) in three primary dimensions. First, we include the BHAR used by Fisch & Momtaz (2020) instead of including the failure rate or exchange listing. Thus, we add a more intangible measurement to their study. Second, our methodology differs from Howell et al. (2020) since we exploit a 2SLS regression alongside a restricted control function to assess the relationship between institutional investors and ICO operational progress. Third, we conduct the research on a data sample with broader timeframe, while also sharing our data sample and Python code on GitHub.

3 Data

In this section, we first present the data used in our paper. Second, we describe the variables in our study. Third, we present the descriptive statistics of our sample.

We combine data from several sources to gather our data set of 853 ICOs between 2014[1] and 2020. The core data, obtained from the Token Offerings Research Database (TORD), consists of 6416 hand-collected ICOs, IEOs, and STOs, issued between 2014-21 (Momtaz, 2021). In this paper, we focus the research on issued ICOs, which corresponds to a total sample of 5979 in the TORD. As of January 2021, the TORD is more comprehensive than any publicly available token

[1] In the sample only three ICOs are issued in 2014 and four in 2015, see figure 1

offerings database (Momtaz, 2021). The reason for the reduction of the data sample is further discussed in section 3.1.

3.1 Variables

Table 1, summarizes the variables, descriptions, and data sources, respectively. We collect the variables expert rating, platform-based business model, token supply, pre-sale and ICO whitepaper from the TORD. We also add several hand-collected variables to our data sample with data from CoinMarketCap, ICObench, LinkedIn and Crunchbase.

Using this labour-intensive approach, we identify a sample of 428 ICOs with complete information and a sample of 853 ICOs with partial information. In our final sample we only have missing values for expert rating, token supply and employment during the ICO. We choose to fill the missing values with the sample's median (see appendices Figure 1-6). Since the quantity of ICOs in our sample is large including some outliers[2], filling the missing values with the median is preferable over the sample's mean. Moreover, for the variables employment during the ICO and expert rating the difference between the mean and median is very small.

We use a set of control variables on issuer characteristics and human capital characteristics that has demonstrated a significant impact on ICO success in prior literature (e.g. Fisch, 2019; Fisch & Momtaz, 2020; Howell et al., 2020). Most of our control variables is included due to significant values in prior literature, while some variables are included because of relevance for our research.

Table 1
Variable Definitions

Variable	Definition	Data source(s)
A. ICO performance measurements		
BHAR	Market-weighted Buy-and-Hold Abnormal Return (BHAR) measured over the first 180 days of trading after the token's first trading day.	CoinMarketCap
Employment during ICO	Number of team members during the ICO.	LinkedIn, ICObench & Ventures websites
Post-ICO employment	Number of team members measured 180 days after the ICO.	LinkedIn, ICObench & Ventures websites
Employment growth	Employment growth measured as the difference between the employment during the ICO and post-ICO employment.	LinkedIn, ICObench & Ventures websites
B. Issuer characteristics		
Institutional investors (dummy)	Dummy variable equal to one if the ICO is institutional investor backed, zero otherwise.	Crunchbase, ventures websites

(continued)

[2] We have some extreme outliers in the token supply, meaning there are extreme values that are not in line with the rest of the sample, see figure A.7 in appendices. Using the mean would be misleading due to the outliers. Dealing with outliers is common within ICO research (see e.g., Fisch 2019; Roosenboom et al., 2020).

Table 1 - Continued

Variable	Definition	Data source(s)
Whitepaper (dummy)	Dummy variable equal to one if the venture published a whitepaper prior to the ICO, zero otherwise.	TORD
Pre-sale (dummy)	Dummy variable equal to one if a pre-sale was issued prior to the actual ICO, zero otherwise.	TORD
Platform (dummy)	Dummy variable equal to one if the venture has a platform-based business model, zero otherwise.	ICObench
Token supply (log.)	Number of tokens (log.) created in the smart contract used in the token offering.	TORD
Expert rating (log.)	Expert ratings of the project at the time of the ICO. Rating scale from 1 ("low quality") to 5 ("high quality").	TORD
Utility token (dummy)	Dummy variable equal to one if the tokens in the ICO has utility value, zero otherwise.	ICObench
C. Human capital characteristics		
Entrepreneur experience (dummy)	Dummy variable equal to one if the founder has an entrepreneurial professional background before founding the ICO venture, zero otherwise.	LinkedIn, venture websites
Computer science experience (dummy)	Dummy variable equal to one if the founder has a professional background in computer science before founding the ICO venture, zero otherwise.	LinkedIn, venture website
Finance experience (dummy)	Dummy variable equal to one if the founder has a professional background in finance before founding the ICO venture, zero otherwise.	LinkedIn, venture websites
Female (dummy)	Dummy variable equal to one if a female was a member of the ICO team prior to and during the ICO, zero otherwise.	LinkedIn, venture websites

ICO Performance. As our dependent variables in the final model, we use the Buy and Hold Abnormal Return (BHAR), post-ICO employment, employment during the ICO and employment growth. To obtain the data to calculate the BHAR, we use an API provided by CoinMarketCap. By manually collecting the correct ICO start dates and coding in python[3], we retrieve each ICO's price and market capitalization as of day 1 and day 180 from the API. CoinMarketCap is a leading source of cryptocurrency volume and price data, aggregating information from over 500 major exchanges (CoinMarketCap, 2022). Only a fraction of the ICOs in the TORD has a CoinMarketCap identifier[4], which is needed to identify each ICO in the database, narrowing the sample from 5979 to 1281 ICOs. Our final sample of complete performance data consists of 1150 ICOs. The further narrowing of the sample is due to three primary reasons. First, CoinMarketCap do not hold any information for some ICOs with an identifier. A possible explanation is that CoinMarketCap continuously removes tokens that show fraudulent tendencies or provide misleading information (Roosenboom et al., 2020). Second, some tokens do not exist 180 days after the ICO start date. Therefore, the $P_{t=180}$ is not available for some tokens, which is required

[3] We collect the correct start dates manually since CoinMarketCap continuously deletes fraudulent or failing tokens. However, historical token data still exists in CoinMarketCap's database.
[4] We ensure that we collect all available ICOs on CoinMarketCap by crosschecking all tokens in the API with the TORD.

when calculating the BHAR. Third, some tokens have an initial price ($P_{t=1}$) equal to zero, which does not hold mathematically when dividing with $P_{t=1}$ in the BHAR formula.

Substantial sample reduction is common when relying on performance data, such as prices and market capitalization in ICO research. Lyandres et al.'s (2019) initial sample was reduced from 4441 to 2905 ICOs when considering the aftermarket performance. Similarly, Fisch & Momtaz (2020) sample was gradually narrowed from 2905 to 565 ICOs as all the data was collected. While a reduction in sample size is not an uncommon concern, it is a limitation that we discuss further down in section 6.2.

The BHAR measures the gains in wealth for investors who holds the tokens for 180 days after the first trading day. To calculate the BHAR we use the formula specified below following Fisch & Momtaz (2020):

$$BHAR_i = \frac{P_{i,\,t=180} - P_{i,t=1}}{P_{i,t=1}} - \sum_{j=1\, j\neq i}^{n} \frac{MktCap_{j,t=180}}{\sum_{j=1}^{n} MktCap_{j,t=180}} \times \frac{P_{j,\,t=180} - P_{j,t=1}}{P_{j,t=1}} \tag{1}$$

where $P_{i,t}$ is the token price of firm *i* on day t. $MktCap_{j,t}$ is the market capitalization of firm *j* on day *t* (and $j \neq i$). The BHAR is adjusted with a market-capitalization-based benchmark, further motivated by Fisch & Momtaz (2020). We calculate the BHAR through coding in python.

Furthermore, we calculate the BHAR over six months, like prior ICO research (Fisch & Momtaz, 2020). Fisch & Momtaz (2020) compute a monthly performance measure (BHAR) for several holding periods ranging from one to twelve months. They conclude that the BHAR based on six months covers most of the value creation by institutional investors. Therefore, we have not calculated the BHAR over several periods and only focus our primary analysis on a six-month performance measure.

We retrieve the hand-collected variable; post-ICO employment from LinkedIn, ICObench, and the ICO issuer's websites. However, we retrieve employment during the ICO from the TORD. LinkedIn is a trusted source due to its global use (Howell et al., 2020). ICObench is used in several earlier studies due to its comprehensive coverage (see e.g., Lyandres et al., 2019; Fisch & Momtaz, 2020). The data sample is further reduced due to the absence of LinkedIn pages. The final data sample consists of 853 ICOs. We calculate the employment growth 180-days after the ICO end date with the following formula;

$$\text{Employee Growth}_i = \frac{\left(\frac{\log(\text{Employees Today}_i+1)}{\log(\text{Number of Days Since ICO Ended})} \times \log(180)\right) - \log(\text{Old Employees}_i+1)}{\log(\text{Old Employees}_i+1)}$$

(2)

To retrieve the employment growth from the formula above, we use the number of employees as of April 2022 from LinkedIn. Since the number of days since each ICO ended varies, we normalize the sample by dividing the number of employees today with the number of days since the ICO end date, multiplied by 180 days. In that way we obtain the number of employees 180 days after each ICO ended.

Issuer Characteristics. The independent variable in our research is institutional investors, which we create as a dummy variable. The dummy equals one if an ICO received an investment from an institutional investor (e.g., venture capitalists or hedge funds) and zero otherwise (Brav & Gompers, 1997; Colombo and Grilli, 2010; Howell et al., 2020; Fisch & Momtaz, 2020). We hand-collect this variable from CrunchBase, the leading provider of private-company research solutions and prospecting (Żbikowski & Antosiuk, 2021). To verify the accuracy of the data provided by Crunchbase we manually cross-check each ICO's website.

We base our independent variable solely on commercial information provided by CrunchBase, while Fisch & Momtaz (2020) create their institutional investor variable on partly commercial and partly proprietary information (Momtaz, 2022a). As a result of the limited access to investor data our sample is different from theirs, which is an important note to consider when reading our paper. See further explanation in section 6.2.

As our control variables within issuer characteristics, we have included the existence of a whitepaper prior to the ICO since earlier research finds that whitepapers effectively diminish the information asymmetry within the ICO market (Zhang et al., 2019). According to Howell et al. (2020) whitepapers positively impacts the number of employees during the ICO.

Pre-sale is a control variable in our research as it has a significant influence on the BHAR in previous research (Fisch & Momtaz, 2020). A pre-sale allows investors to get a discount on the tokens but can also be used to investigate the token demand or to gain promotion for the public ICO (Derrien & Womack, 2003). Pre-sale is a relevant variable since prior research indicates that investors participating in a pre-sale, also referred to as early investors, are crucial for the ICO performance (Fisch, 2019).

A platform-oriented business model can facilitate future venture growth (Harvard Business Review, 2021). Fisch & Momtaz's (2020) research further indicates that a platform-based business model is positively linked to investor backing as institutional investors look for ventures with high growth potential (e.g., Block et al., 2019; Puri & Zarutskie, 2012). Therefore, we include the platform dummy variable in our research.

ICO expert ratings issued by cryptocurrency experts has a positive impact on ICO fundraising and ICO performance (Roosenboom et al., 2020). Therefore, we include expert ratings issued by ICObench in our research. Even though the variable does not indicate a significant impact on post-ICO performance in Fisch & Momtaz's (2020) final model, we consider this variable to be of relevance for our research since earlier research indicate a positive relationship between ICO success and expert ratings (Roosenboom et al., 2020). Furthermore, we include this variable since expert ratings mitigate the information asymmetry related to token sales (Roosenboom et al., 2020). The ratings are based on team, vision, and product, on a scale from 1 ("low quality") to 5 ("high quality") (Fisch & Momtaz, 2020). We create a logarithmic variable of the expert rating for each ICO.

There is a specific token supply in all issued ICOs, like shares in an IPO (Sturla, 2019). We use the token supply as a control variable since it is of relevance when explaining institutional investor backing. Furthermore, this variable indicates a significant influence on post-ICO performance in two of Fisch & Momtaz (2020) robustness tests. Therefore, we consider this variable to be of relevance for our research since we have a different data sample with a broader timeframe compared to Fisch & Momtaz (2020). We create a logarithmic variable of the token supply.

Utility tokens are tokens that give investors so-called corporate coupons. These coupons provide safety by giving the consumptive privilege to access the issuer's service or product (Howell et al., 2020). We include utility tokens as a control variable in this paper since Howell et al. (2020) finds that utility value in an ICO token is of importance.

Human capital characteristics. Prior literature finds empirical evidence that emphasize the importance of human capital for venture success (see e.g., Hsu, 2007; Unger et al., 2011). Previous studies also uncover that venture founders with previous experience in entrepreneurship often are more successful, regardless of if the founder's previous start-up experience was successful or not (Flynn, 1991; Gimmon & Levie, 2009). Another sort of founder experience that the literature acknowledges is prior industry background and knowledge (MacMillan, 1986; Kaplan & Strömberg, 2004; Colombo et al, 2004). Howell et al. (2020) find that a technical background in computer science positively impacts ICO success. Therefore, we include three dummy variables of founder experience in computer science, entrepreneurship, and finance. We create these variables by manually collecting data from LinkedIn, ICObench, and the ICO issuer's websites.

Prior literature on gender diversity within the ICO industry finds that women are underrepresented (Guzman et al., 2021). Moreover, Guzman et al. (2021) finds evidence that ICO projects with females in their teams raise a higher total funding amount. In other words, a positive relationship between female involvement in the ICO issuer's team and funding amount is confirmed. Moreover, Howell et al. (2020) found a slight link between ICO failure and male participation in the ICO process. Therefore, we include a dummy variable of the presence of a female in the team prior and during the ICO. The dummy equals one if the issuer had a female employee prior and during the ICO, zero otherwise. We create this variable by manually reviewing each ICO's team page on LinkedIn.

3.2 Descriptive statistics

Table 2 displays a summary of descriptive statistics for our sample.

Table 2
Descriptive Statistics

	N	Mean	SD	Median	Min	Max
A. Post-ICO performance						
BHAR	853	0.02	2.98	-0.10	-0.11	86.89
Employment during ICO	853	12.33	7.44	11.00	1.00	66.00
Post-ICO employees	853	45.14	353.62	9.00	0.00	6761.00
Employee growth	853	4.60	45.62	0.00	-1.00	989.75
B. Issuer characteristics						
Institutional investor	853	0.27	0.44	0.00	0.00	1.00
Whitepapers	853	0.91	0.29	1.00	0.00	1.00
Pre-sale	853	0.38	0.48	0.00	0.00	1.00
Platform	853	0.57	0.50	1.00	0.00	1.00
Token supply (log)	853	8.37	0.90	8.36	3.00	13.48
Expert rating (log)	853	0.50	0.10	0.51	-0.15	0.69
Utility token	853	0.90	0.30	1.00	0.00	1.00

(continued)

Table 2 – Continued

	N	Mean	SD	Median	Min	Max
C. Human capital characteristics						
Entrepreneur exp.	853	0.41	0.49	0.00	0.00	1.00
Computer science exp.	853	0.23	0.42	0.00	0.00	1.00
Finance exp.	853	0.13	0.33	0.00	0.00	1.00
Female	853	0.46	0.50	0.00	0.00	1.00

This table demonstrates an overview of our sample statistics consisting of 853 initial coin offerings. The outline presents the mean, standard deviation, median, minimum, and maximum of each variable. Panel A displays the dependent variables that measure ICO performance. Panel B displays the issuer characteristics. Panel C displays the human capital characteristics. For all panels, data was gathered from the TORD, ventures websites, ICO bench and LinkedIn.

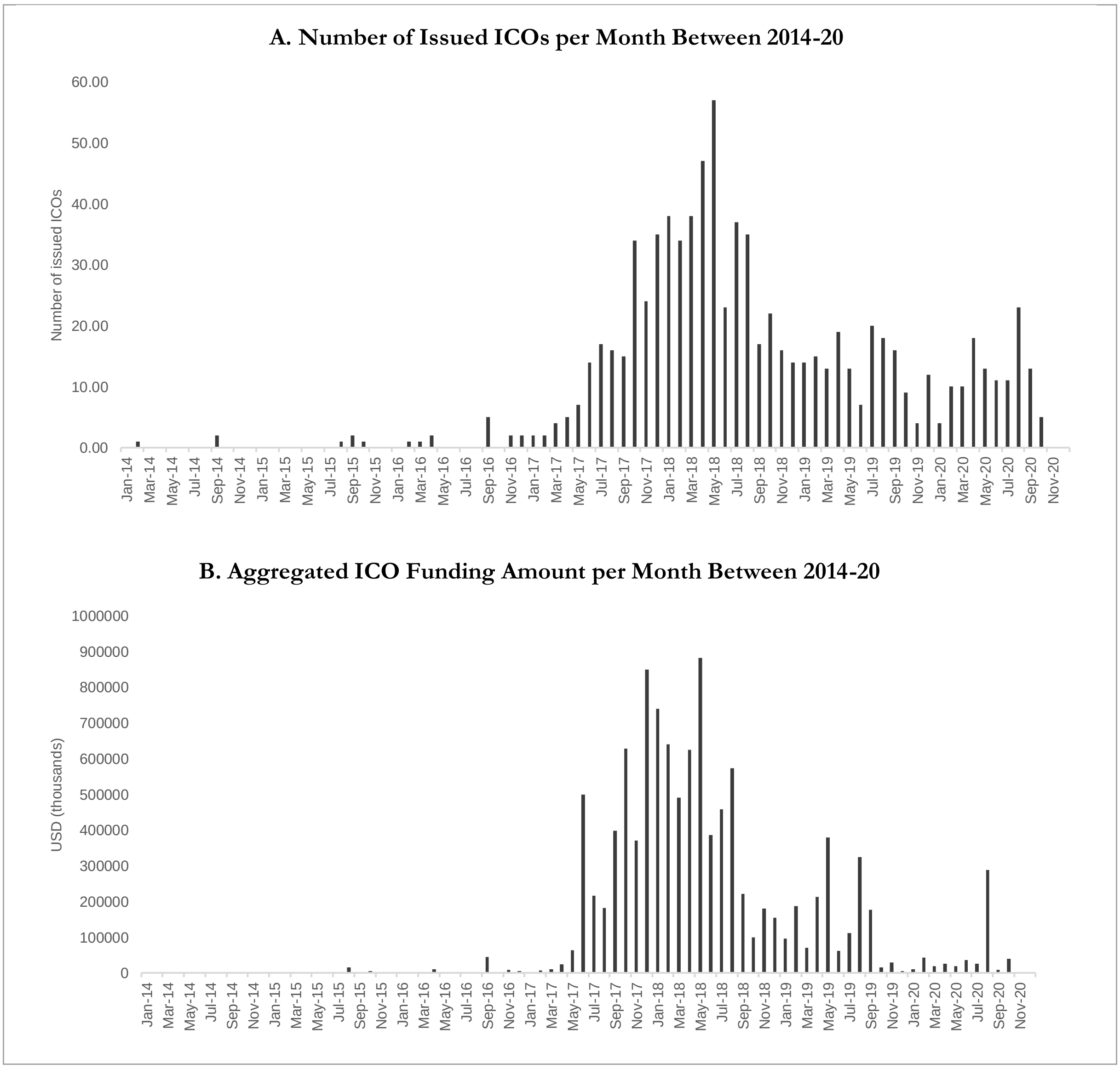

Figure 1
Figure 1.A displays the total number of ICOs issued per month between 2014-20 for our sample of 853 ICOS. Figure 1.B displays the total aggregated funding amount in thousand USD per month between 2014-20. The funding amount raised is only available for 494 of the ICOs in our sample, which are the ones included in the graph.

Figure 1A presents the number of issued ICOs per month between the years 2014-20 in our sample. Consequently, Figure 1.B displays the aggregated funding amount per month between the years 2014-20 in USD (in thousands).

In our sample, 231 of the total 853 ICOs obtained institutional investor backing, corresponding to 27.5% of our sample, consistent with the findings of Fisch & Momtaz (2020). Furthermore, our sample yields an average BHAR corresponding to 2.2%, with a standard deviation of 2.98. In contrast, Fisch & Momtaz (2020) presents an average BHAR of 26.5%, with a standard deviation of 3.8. Five possible factors can explain this significant difference in average BHAR. First, our sample is different from the sample used by Fisch & Momtaz (2020) since we construct a dataset with an extended timeframe. The diverse data sample can explain the discrepancy between our average BHAR and their average BHAR. Second, since Fisch & Momtaz (2020) conducted their research in 2020, CoinMarketCap has expanded significantly, increasing the aggregated data from 26 to 522 cryptocurrency exchange listings (Momtaz, 2022; CoinMarketCap, 2022). The substantial upsurge of exchange listings enables CoinMarketCap to access more high-quality, in-depth data on different projects (CoinMarketCap, 2022).

Additionally, CoinMarketCap continuously remove tokens that provides misleading information, shows tendencies of fraudulent activity, or fails (Roosenboom et al., 2020). Thus, the data we obtain from CoinMarketCap could potentially be different from the data Fisch & Momtaz (2020) use. Third, there is approximately a 20% overlap between CoinMarketCap and ICOBench, on which the TORD is based (Momtaz, 2019). Therefore, there is a discrepancy between ca 52% of the start dates in the TORD and those available on CoinMarketCap, which indicates that there is a possibility that we use different start dates, as we use the start dates provided CoinMarketCap[5].

Forth, Fisch & Momtaz (2020) has a standard deviation of 3.8, which corresponds to a 0.8 points higher standard deviation than ours, indicating that they may have a higher number of outliers that potentially could increase the BHAR. Fifth, our sample is more extensive, which means that the weighted benchmark in our BHAR formula is larger, comparing 853 ICOs in our calculations with 565 ICOs used in their calculations.

The average number of employees during the ICO is 12.33, while the average number of employees post-ICO is 45.14, and the average employment growth is 460%. All variable statistics presented above are aligned with the statistics presented by Fisch & Momtaz (2020). Moreover, the average number of employees during the ICO is similar to Howell et al. (2020). However, we

[5] CoinMarketCap confirmed by e-mail (CoinMarketCap, 2022) that the first day available in their database is the first trading day of the token.

yield different results on the post-ICO employment and employment growth due to the different timeframes, as we have a data sample with a broader timeframe.

The logarithmic mean of expert rating corresponds to 0.5. The average logarithmic value of token supply is 8.37. Moreover, 37.3% of the ventures in our sample conducted a pre-sale before the public ICO. For the sample, the mean of whitepapers is 91%, while 90% have a utility token. Furthermore, 57% have a platform-based business model.

Table 3 displays the correlation between all variables in our data sample (see section 3.1). All correlations except the correlation between employment growth and post-ICO employment are below the critical level of +/- 0.7 (Fisch & Momtaz, 2020). Values above the critical level of 0.7 indicate a high correlation between two variables, meaning that multicollinearity exists within the sample. Multicollinearity implies that the independent variable's influence on the dependent variable cannot be explained (Alin, 2010). Since employment growth are calculated based on both the employment during the ICO and post-ICO employment, the significant correlation that we obtain is not surprising since they are based on the same numbers. As we never use post-ICO employment and employment growth in the same regressions, the multicollinearity is not an issue for our research.

Table 3
Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. BHAR														
2. ICO Employees	-.03													
3. Post-ICO Employees	.01	-.01												
4. Employment growth	.00	-.09*	.89**											
5. Institutional investor	-.02	.05	-.01	-.01										
6. Whitepapers	.01	.07	-.18**	-.18**	-.03									
7. Pre-sale	.04	.13**	-.05	-.06	-.15**	.12**								
8. Platform	.03	.08*	-.02	-.05	-.08*	-.04	.06							
9. Token supply (log)	-.00	.15**	.04	.00	.06	.01	.03	.10**						
10. Expert rating (log)	.00	.22**	-.04	-.02	.00	.28**	.34**	.03	.15**					
11. Utility token	.01	.11**	.00	-.04	-.04	.07*	.15**	.27**	.01	.02				
12. Entrepreneur experience	-.03	.09*	.10**	.11**	.19**	-.03	-.07*	-.01	.05	.10**	.01			
13. Computer science experience	-.02	.07*	.13**	.14**	.14**	-.01	.01	.02	.03	.06	.03	.13**		
14. Finance experience	-.01	.02	.06	.04	.03	-.01	-.01	-.00	.01	.04	-.02	.09**	-.01	
15. Female	-.03	.12**	.11**	.11**	.14**	-.04	-.00	.04	.15**	.10**	-.01	.15**	.10**	.11**

Note: * indicates $p < .05$. ** indicates $p < .01$

4 Model

4.1 Potential Endogeneity in the Sample

To replicate Fisch & Momtaz's (2020) methodology to investigate our empirical question of how institutional investors impact ICO performance, we conduct a Two-Stage Least Squares (2SLS) regression with a Restricted Control Function (rCF) approach. This methodology deals with the possible endogeneity in our sample, specifically between the institutional investor variable and the error term. The endogeneity issue arises because institutional investors might target high-quality investments in the first place. Institutional investor's superior selection of ventures is potentially because they have access to or produce private information regarding venture quality in their screening processes (Fisch & Momtaz, 2020).

Since our research is based on publicly available information, we must consider the potential selection bias that may affect the actual influence of institutional investors on post-ICO performance (Colombo & Grilli, 2008; Fisch & Momtaz, 2020). Furthermore, Bertoni et al., (2011) argues that new technology-based venture's performance is very influenced by unobservable characteristics that cannot or is difficult to translate into tangible measurements. Such unobservable characteristics could relate to an innovative business idea, the intelligence of the business management and the uniqueness of the technology. Therefore, these unobservable characteristics may also influence the post-ICO performance and the probability of institutional investor backing. Previous literature on institutional investors further emphasizes the importance of exploiting a methodology that accounts for these potential biases (Colombo & Grilli, 2008; Bertoni et al., 2011; Chemmanur et al., 2011; Guo and Jiang, 2013; Fisch & Momtaz, 2020). If one fails to account for these biases, the results may indicate an overestimation of institutional investors' actual impact on post-ICO performance.

4.2 Econometrical Approach

To address the relationship between institutional investors and post-ICO performance, the initial baseline regression we run is given in equation (3) following Fisch & Momtaz (2020). We seek to estimate the effect of institutional investor backing for firm i ($INST_i$) on post-ICO performance measured by the BHAR ($BHAR_i$), post-ICO employment (E_i), employment during ICO (OE_i) and employment growth (Eg_i) controlling for a vector of independent variables, Ωi. Y_i denotes the dependent variable, replaced by $BHAR_i$, E_i, OE_i and Eg_i in each regression:

$$Y_i = \beta INST_i + \Omega_i\gamma + \varepsilon_i$$

(3)

Before conducting the rCF we run a first-stage regression (2), referred to as the selection equation, which models the probability that firm *i* receives institutional investor backing by a vector of exogenous control variables affecting the selection mechanism, $\Omega i^{(s)}$. As the data sample does not include any instrumental variables to explain the institutional investors variable, this equation allows us to estimate $INST_i$ by a vector of all the control variables. The formula includes the error term since the control variables do not have enough explanatory value to fully explain $INST_i$.

$$INST_i = \Omega i^{(s)}\delta + \xi_i$$

(4)

4.2.1 Restricted Control Function (rCF)

We adopt a restricted control function (rCF) approach to account for the potential endogeneity between institutional investors and several control variables, following Fisch & Momtaz (2020) and Colombo & Grilli, 2005, 2008, 2010. The rCF generates a generalized residual together with the first-stage equation (4), which can be seen as an explicit test for endogeneity (Colombo & Grilli, 2008; Fisch & Momtaz, 2020). The generalized residual then control for endogeneity in a two-stage process when inserted as a single control variable in equation (3). We use this methodology to obtain more consistent parameter estimates in our performance models. Since Fisch & Momtaz (2020) observe the same results when performing the rCF, inverse mills ratio (IMR), and propensity score matching, we only conduct the rCF and use the IMR as a robustness test. The advantage of using an rCF over an IMR is that it does not assume that the conditioning set of relevant control variables is sufficiently complete. Instead, it models omitted variables (Heckman and Navarro-Lozano, 2004; Fisch & Momtaz, 2020).

To generate the generalized residual (Gourieroux et al., 1987; Fisch & Momtaz, 2020) later used in equation (6), we define the generalized residual as:

$$GENRES_i = INST_i \times \frac{\phi(-\Omega i^{(s)}\delta)}{1-\Phi(-\Omega i^{(s)}\delta)} + (1 - INST_i) \times \frac{-\phi(\Omega i^{(s)}\delta)}{\Phi(-\Omega i^{(s)}\delta)}$$

(5)

where $\phi(.)$ denotes the probability density, and $\Phi(.)$ denotes the cumulative density functions of the standard normal distribution. Whereas the mean and standard deviation equal zero and one, respectively. Inserting the *GENRESi* into eq. (3) as a single control variable results in the following rCF estimator, in which θ strains the null hypothesis that there is no selection effect:

$$Y_i^{rCF} = \beta INST_i + \theta GENRES_i + \Omega_i \gamma + u_i \tag{6}$$

in the case θ is significantly different from zero, meaning that the null hypothesis is rejected, this variable should not be considered in the final model.

5 Empirical Analysis

This section presents the results of our empirical tests. In section 5.1, we present the result of our regressions using the BHAR as the dependent variable. In section 5.2, we present the results of our regressions using post-ICO employment, employment during the ICO and employment growth as dependent variables. In section 5.3, we analyse the drivers of ICO success and how the measurements of post-ICO performance differ. We conclude by presenting robustness checks on our findings in section 5.4.

5.1 ICO Performance: BHAR

This section reports the results of our regressions that uncover the impact of institutional investor backing on post-ICO success measured by the BHAR. We begin our analysis by regressing the institutional investor variable on all ICO control variables. After that, we continue the analysis by regressing the BHAR on the institutional investor variable including the generalized residual. Table 4 reports the results from these first regressions specified below;

$$INST_i = \Omega i^{(s)} \delta + \xi_i \tag{3}$$

$$GENRES_i = INST_i \times \frac{\phi(-\Omega i^{(s)} \delta)}{1-\Phi(-\Omega i^{(s)} \delta)} + (1 - INST_i) \times \frac{-\phi(\Omega i^{(s)} \delta)}{\Phi(-\Omega i^{(s)} \delta)} \tag{5}$$

$$Y_i^{rCF} = \beta INST_i + \theta GENRES_i + \Omega_i \gamma + u_i \tag{6}$$

In column (1), we present the selection model, column (2) presents the control model, and in column (3) we present the performance model using a 2SLS regression with a rCF approach.

Column (1) displays the institutional investor dummy on a vector of observable characteristics, where a regular logistics regression has been used. The results indicate that institutional investor backed ventures are 73,8% (-0,738) less likely to conduct a pre-sale, and 34,2% (-0,342) less probable to have a platform-based model. In contrast, prior literature finds that a platform-based business model increases the odds of attracting investor financing (Fisch & Momtaz, 2020). Moreover, we can observe that the founder's professional experience has a positive relationship with institutional investor backing. Our results indicate that ventures founded by a person with an entrepreneurial background are 70,2% more likely to obtain investor backing. Experience in computer science increases the probability of investor backing by 56,6%. Previous literature in the venture capital and ICO context finds evidence that indicates that a company's founding team is an essential aspect when attracting venture capital investments (Gompers et al. 2016; Bernstein et al., 2017; Howell et al., 2020), which our results further support. We observe no indications that founder experience in finance attracts institutional investors.

Furthermore, our results indicate that a female employee in the team prior and during the ICO has a positive impact on the probability of obtaining institutional investor backing, with a coefficient estimate of 48,7% ($p < .01$). This result implies that a one-point-standard-deviation increase over the female variable increases the probability of attracting institutional investor financing by 73,05% (= 0,487 + 0.487 × 0.5). No significant impact emerges regarding issuing a whitepaper, the size of the token supply, the average expert rating of the ICO, founder finance experience, or the utility value of the token.

In column (2), we test the BHAR in relationship to all the control variables of the model, with the independent variable excluded from the model. Considering these results, column (3) demonstrates the 2SLS regression including the generalized residual. The results in column (3) display that institutional investor-backed ICOs outperform the ones without investor-backing by a rate corresponding to 1096,20% ($p<0,05$) with the selection effect by the generalized residual. This in turn indicates that the institutional investor backed ICOs yields a BHAR 1096,20% higher than the ventures without access to institutional investor capital. Thus, our empirical result further supports the result that Fisch & Momtaz (2020) finds. However, our result indicates a significantly higher impact on post-ICO performance by institutional investors than their result (129%).

We observe no significant relationship between the generalized residual and the BHAR in our rCF model, indicating no selection effect in our sample. Therefore, our results imply that institutional investors do not have a superior capability to identify high-quality ventures when using the BHAR as the dependent variable. However, the null hypothesis still holds, due to a significant relationship with the post-ICO employment and employment growth, see section 5.2.

Furthermore, comparing the results in the control model (column (2)) with the results in the performance model (column (3)), we find observable differences in the coefficients. This implies that endogeneity exists in our sample even though the $GENRES_i$ coefficient is insignificant in our rCF model using the BHAR. The differences between the coefficients in the columns implies that if one neglects the existing endogeneity the results are substantially biased.

By observing the results of the control variables, we find that conducting a pre-sale and a platform-based business model have a positive impact on the BHAR, with 165.70% and 86.90%, respectively. In contrast, founder entrepreneurial background, computer science experience, and female inclusion decrease the post-ICO success with –154.70%, -132,70% and -112,70%, respectively. Using an extended dataset with a broader timeframe with other control variables included can explain why our result differs from the findings by Fisch & Momtaz (2020). Fisch & Momtaz (2020) finds a negative relationship between platform-based business models and the BHAR while presenting a positive relationship between the BHAR and pre-sale.

As Table 4 displays, the control variables only have explanatory power to partly explain the BHAR, with an average R^2 corresponding to 4-10%. Fisch & Momtaz (2020), reports an R^2 between 11,8-14,5% when using a smaller dataset and different variables. Thus, our R^2 further enhances the complexity of explaining ICO success (Bertoni et al., 2011; Fisch & Momtaz, 2020).

5.2 ICO Performance: Employment

This second section reports the results of our regressions that uncover the impact of institutional investor backing on post-ICO success measured by the post-ICO employment, employment during the ICO and employment growth. We begin our analysis by calculating the employment growth presented in section 3.1. We then regress our final model (equation 6) on ICO employment, post-ICO employment, and employment growth, as specified below;

$$Y_i^{rCF} = \beta INST_i + \theta GENRES_i + \Omega_i \gamma + u_i \tag{6}$$

Table 4 displays the results from the regressions on each dependent variable. In column (1), we present the results of the selection model, which are explained in section 5.1. Columns (4), (6), and (8) present the control model results. Finally, columns (5), (7), and (9) present the performance model results using the 2SLS regression with the rCF approach.

The results in columns (5), (7), and (9) show that institutional investor backing positively impact post-ICO employment (+186.70%) and employment growth (+135.20%). The positive influence of institutional investor backing on employment is evident in earlier IPO success literature, such as in Baker & Gompers (2003) and Hochberg (2011). Howell et al. (2020) likewise conclude that post-ICO performance in terms of employment growth has a positive relationship with access to VC equity. We find no significant indications that the number of employees during the ICO influences whether a venture will obtain investor backing or not.

The generalised residual we use to control for the selection bias of institutional investors does generate significant results for post-ICO employment and employment growth. Thus, as described in section 4.2.1, the null hypothesis is not rejected, and the $GENRES_i$ is included in our final regression model. This ultimately indicates that there is a selection effect in our sample, meaning that the institutional investors do have a superior ability to screen and identify high-quality ICO ventures.

The results of the control variables in column (5) indicate that disclosure of a whitepaper and a larger token supply has a negative impact on post-ICO employment, corresponding to -9.80% and –4.90%, respectively. Furthermore, we find that a pre-sale, a platform-based business model and a higher average expert rating positively influence post-ICO employment, with 19.10%, 13.60% and 57.30%, respectively. Cong, Li and Wang (2018) argue that network effects positively impact token prices, meaning that if the number of network users increases, the price will increase accordingly. Similar network effects can be argued to apply a platform-based business model (Harward Business Review, 2021). We also obtain results indicating that founder finance experience (19.80%) and a female on the team prior and during the ICO (28.60%) positively impact post-ICO employment, which align with findings in prior research (see e.g., Howell et al., 2020). We find no influence on post-ICO employment by the founder's experience in computer science or entrepreneurship.

The results in column (7) indicates that a platform-based business model, a larger token supply and a higher expert rating have a positive relationship with the employment during the ICO, corresponding to 5.50%, 2%, and 27.60%, respectively. According to Fisch & Momtaz (2020) and Roosenboom et al. (2020), a platform-based business model and a high expert rating can signal credibility and professionalism. These signalling effects could therefore attract human capital to the ICO team.

Observing the results in column (9), we can conclude that ventures issuing a larger token supply obtain a lower employment growth corresponding to -6.90%. Furthermore, founder finance experience and female inclusion positively impact employment growth with 10.60% and 20.50%, respectively. Thus, our results further support the findings by Howell et al. (2020), emphasizing the importance of team gender diversity for ICO-success.

Table 4

Institutional Investor Backing and ICO-performance

	Dependent variable:								
	Institutional investor	BHAR		Post-ICO Employment		Employment during ICO		Employment growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Institutional investor			10.962**		1.867***		0.267		1.352*
			(4.832)		(0.708)		(0.392)		(0.799)
Generalized residual			YES		YES***		YES		YES***
			(+)		(+)		(+)		(+)
Whitepapers	-0.082	0.077	0.281	-0.137**	-0.098*	0.005	0.010	-0.091	-0.063
	(0.280)	(0.366)	(0.376)	(0.054)	(0.055)	(0.030)	(0.031)	(0.061)	(0.062)
Pre-sale	-0.738***	0.256	1.657**	-0.069**	0.191**	0.047**	0.083	-0.119***	0.069
	(0.187)	(0.227)	(0.658)	(0.034)	(0.096)	(0.018)	(0.053)	(0.038)	(0.109)
Platform	-0.342**	0.168	0.869**	0.005	0.136**	0.037**	0.055*	-0.023	0.071
	(0.163)	(0.209)	(0.373)	(0.031)	(0.055)	(0.017)	(0.030)	(0.035)	(0.062)
Token supply (log)	0.107	0.008	-0.203	-0.009	-0.049**	0.026***	0.020*	-0.041**	-0.069***
	(0.092)	(0.116)	(0.149)	(0.017)	(0.022)	(0.009)	(0.012)	(0.019)	(0.025)
Expert rating (log)	0.490	-0.380	-1.348	0.753***	0.573***	0.301***	0.276***	0.437**	0.307
	(0.908)	(1.152)	(1.227)	(0.171)	(0.180)	(0.093)	(0.100)	(0.191)	(0.203)
Utility token	-0.187	0.073	0.421	-0.020	0.044	0.016	0.024	-0.066	-0.020
	(0.257)	(0.339)	(0.371)	(0.050)	(0.054)	(0.027)	(0.030)	(0.056)	(0.061)
Entrepreneur experience	0.702***	-0.096	-1.547**	0.287***	0.016	0.032*	-0.005	0.199***	0.004
	(0.165)	(0.216)	(0.675)	(0.032)	(0.099)	(0.017)	(0.055)	(0.036)	(0.112)
Computer science experience	0.566***	-0.096	-1.327**	0.248***	0.017	0.026	-0.005	0.168***	0.001
	(0.182)	(0.248)	(0.596)	(0.037)	(0.087)	(0.020)	(0.048)	(0.041)	(0.099)
Finance experience	0.026	-0.087	-0.134	0.207***	0.198***	0.009	0.007	0.113**	0.106**
	(0.236)	(0.310)	(0.310)	(0.046)	(0.045)	(0.025)	(0.025)	(0.051)	(0.051)
Female	0.487***	-0.162	-1.127**	0.465***	0.286***	0.033*	0.008	0.334***	0.205***
	(0.166)	(0.213)	(0.475)	(0.032)	(0.070)	(0.017)	(0.039)	(0.035)	(0.079)
Observations	853	853	853	853	853	853	853	853	853
R^2		0.004	0.010	0.394	0.414	0.072	0.073	0.204	0.214

This table presents the results of our final model, using a 2SLS with a restricted control function (rCF) approach. Column (1) presents the first-stage regression ($INST_i=\Omega_i^{(s)}\delta+\xi_i$) which estimates the institutional investor variable which is regressed on a vector of the control variables included in the paper. Column (2), (4), (6) & (8) presents the regression of the dependent variables on a vector of the control variables. Column (3), (5), (7) & (9) regresses the second-stage and include the generalized residual to employ a restricted control function approach ($Y_i^{rCF}=\beta INST_i+\theta GENRES_i+\Omega_i\gamma+u_i$). All variables are defined in Table 1. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.

The R^2 of these regressions indicates that our variables have an explanatory value between 7.20-41.40%. We retrieve a high R^2 for post-ICO employment corresponding to 41.40%.

5.3 ICO Performance

In this third section of the empirical analysis, we attempt to uncover the drivers of ICO success and how the performance measurements differentiate. Furthermore, we examine the similarities and differences between the ICO-success factors obtained in the results presented in sections 5.1 and 5.2.

Our results indicate that institutional investor backing positively impacts the BHAR, the post-ICO employment and employment growth. Since we obtain significant results indicating a positive impact of institutional investor backing on post-ICO performance, for both the intangible and the tangible measurements, we can conclude that this variable impacts ICO success in terms of investor return and the future operational progress of the venture. In addition, we find no significant relationship between the employment during the ICO and institutional investors. This result indicates that institutional investor backed ventures do not necessarily need to have a big team during the ICO. Therefore, the number of employees during the ICO may not be an ideal factor to predict the ICO venture's future performance.

A platform-based business model and issuing a pre-sale are additional factors that seem to be of importance to post-ICO performance. We can observe that a pre-sale influences the return of the token (BHAR) while also contributing to a higher post-ICO employment. Thus, using a pre-sale to assess the token demand and promote the official ICO can be an essential part of the ICO process to become successful after the ICO. Moreover, a platform-based business model seems favourable in today's society (Harward Business Review, 2021), which is further emphasized in our results as these ventures yield a higher investor return (BHAR) and post-ICO employment.

Expert rating, founder characteristics, and team gender diversity seem to have divergent impacts on the different post-ICO measurements. While expert ratings significantly positively impact post-ICO employment and employment during ICO, we obtain a negative coefficient for the expert ratings variable in the BHAR regression. The founder characteristics also display similar relationships to the different measurements; a positive relationship to post-ICO employment and employment growth while indicating a negative relationship to the BHAR. Therefore, we can conclude that while the founder characteristics are important when attracting human capital, it has no positive consequence on the token return.

A surprising indication of our results is that the team's gender diversity prior to the ICO has a significant negative influence on the BHAR and a significantly positive impact on post-ICO employment and employment growth. Therefore, having a female on the team seems essential when expanding through recruitment but does not necessarily result in a higher return for the ICO investors. A possible explanation for this could be that employee candidates value and consider the team dynamics when accepting employment at a new company. However, gender diversity is not an equally important aspect when investors select ventures to invest in. Our results are similar to Howell et al.'s (2020) findings which also reveal a positive link between gender diversity and post-ICO employment and employment growth.

Because of the divergent influence of the control variables on the performance measurements, we can conclude that ICO elements affect post-ICO success differently depending on what aspect of success one focuses on. When measuring the post-ICO performance with the BHAR, the investor return is in focus and the venture's operational performance, such as attracting human capital, is not considered fully. By observing our sample, we can further conclude that the ventures yielding a higher BHAR do not necessarily have a high employment growth, and the other way around. A token yielding a high BHAR in our sample can result from a slight price increase. If the issuing token price is significantly low, the increase does not have to be that prominent to generate a high BHAR (see equation 1).

Considering the unreliability of the prices surrounding cryptocurrencies and that token prices can be heavily influenced by fraudulent trading activities and artificial enlargement of trading volumes (Corbet et al., 2018; Baydakova, 2019; Howell et al., 2020; Fisch & Momtaz, 2020), measuring the post-ICO success with the BHAR might result in a skewed demonstration of how successful the venture's operations really are. Since the cryptocurrency market is exceptionally volatile, the BHAR measurement is very dependent on the timeframe on which it is calculated. According to Lee & Parlour (2022), the ICO market is influenced by investor speculations. Thus, the token prices do not always reflect the actual value of the token and are commonly overvalued. Therefore, the BHAR is not an entirely reliable measurement since it is based on token prices and ICO market capitalization. Moreover, since we obtain significant results for the generalized residual in all regressions except the one with the BHAR. This further indicates that the BHAR may not be an ideal ICO performance measurement. Thus, from a long-term perspective, ICO issuing ventures displaying a high post-ICO employment and employment growth might better portray ICO success when considering traditional established success factors such as market establishment, value creation, and operational progress (Bruderl and Preisendorfer, 1998; Reid and Smith, 2000; Howell et al., 2020).

5.4 Robustness Test

To reassure the robustness of our empirical findings, we perform an additional test. The resulting table is available in appendices B, Table B1, for reference. First, we conduct a re-estimation of the performance model (see Table 4) using an alternative econometric approach, the inverse mills ratio (IMR). If there is no relevant omitted variable in the model, the IMR softens the assumptions regarding the exogeneity in our sample's regressors and the separability of outcomes (Heckman & Navarro-Lozano, 2004; Fisch & Momtaz, 2020). The model in Table B1 is identical to our final model, except the IMR is included as a single control variable instead of the generalized residual. We primarily conduct this robustness test to ensure that the institutional investor's selection effect cannot be rejected, when exploiting a different method than the rCF. Furthermore, we want to establish that we obtain similar results for our variables, with the same level of significance for the institutional investor variable using a different approach than the one used in our primary model.

We find that the IMR variable is significantly different from zero for post-ICO employment and employment growth, which aligns with our previous results performing the rCF. Thus, this result further indicates that the selection effect cannot be rejected, and that the $GENRES_i$ should be considered in our final model. Moreover, the coefficients of the control variables in the IMR regression yields similar results as in the performance model with the rCF approach (see Table 4). Lastly, our R^2 is nearly the same for the two models, predicting that the final model is robust.

6 Conclusion

6.1 Summary and Concluding Remarks

In this paper, we find that institutional investor backing is an essential factor to account for when predicting ICO performance. Our research indicates that institutional investor backing in an ICO will result in a higher BHAR, post-ICO employment and employment growth. Therefore, we conclude that institutional investor backing partly mitigates the information asymmetry through value signalling within the ICO market. Moreover, we conclude that there is a selection effect in our sample, meaning that the institutional investors do have a superior ability to screen and identify high-quality ICO ventures. Furthermore, issuing a pre-sale and having a platform-based business model may have a positive impact on the venture's BHAR and post-ICO employment.

Our results implicate that ICO elements affect post-ICO performance measurements differently depending on what aspect of success one focuses on. Due to the high volatility surrounding the cryptocurrency market and the fact that ICO token prices are argued to be influenced by fraudulent trading activities, we conclude that more tangible measurements such as post-ICO employment and employment growth are more favourable when predicting ICO success. Such tangible performance measurements better account for traditionally established success factors such as market establishment, value creation, and operational progress. Thus, the BHAR might not be an ideal measurement of ICO performance, at least not until the ICO market data is more standardized and regulated.

Our paper contributes with important implications for the ICO market. Our research indicates that ICO success should be measured with more tangible measurement until the market information is more standardized and disclosure duties are established. We reach this conclusion examining the market between 2014-20, establishing that it is still a young, transforming market that is significantly volatile.

This paper eases future distinction between potential successful ICOs from those ICOs channelling money to recipients for their personal uses. This contribution is especially important for retail ICO investors that do not have access to superior screening material. Our insights regarding drivers of ICO success are also beneficial for future ICO issuers and their stakeholders.

To conclude, our findings imply that institutional investors indeed affect the performance outcome of an ICO, and that institutional investor backing can mitigate the information asymmetries within the ICO market through value signalling.

6.2 Limitations and Future Research

This section discusses the limitations of our research and what future research could further contribute with to the ICO literature by filling these gaps. First, since cryptocurrency-based companies do not have any obligations to list their tokens, the availability of token data is limited. Our sample is therefore dependent on tokens that are exchange listed or tracked by CoinMarketCap. Since we also build our employment variable on data from LinkedIn, we are also dependent on the availability of company's presence on LinkedIn. The dependency on data provided by CoinMarketCap and LinkedIn creates a biased sample consisting of a fraction of all ICOs issued since 2013. We present the division of our sample in appendices A, Figure 1-6. Furthermore, the limited ICO data results in missing values in our sample. We fill these missing values with the sample's median, which potentially could affect the solidity of the results. Also, filling the missing values in this way may influence the model since the cryptocurrency market is very volatile.

Second, the reliability of the prices surrounding cryptocurrencies has been questioned in prior research (Corbet et al., 2018; Howell et al., 2020; Fisch & Momtaz, 2020). Evidence indicates that token prices can be heavily impacted due to fraudulent trading activities and artificial enlargement of trading volumes (Baydakova, 2019). Therefore, the BHAR could potentially lead to skewed results.

Third, our data sample is significantly reduced since the overlap between existing data sources is narrow. According to Momtaz (2019), the overlap between ICObench and CoinMarketCap was approximately 20% in 2019. The poor overlap between data sources creates a discrepancy between data provided in the TORD, upon which this study is partly built, and data provided by CoinMarketCap. This inconsistency could potentially cause differences between our results and results in prior research. Moreover, it is expected that databases such as CoinMarketCap and ICObench delete records of ICOs that are unsuccessful or turn out to be scams. Since our empirical analysis focuses on ICO success and what factors that create the most value for investors, this is not a major issue in our study. However, this is still something to consider when reading our paper.

Forth, due to the poor overlap between the data sources, we detected a discrepancy between the ICO start dates provided in the TORD (taken from ICObench) and the first trading day available on CoinMarketCap. Therefore, we chose to use the first trading day according to CoinMarketCap when calculating the BHAR. In turn, we may have based the BHAR measurement on different prices than Fisch & Momtaz (2020), which potentially causes different results.

Fifth, most of the control variables are included in our paper due to significant value in prior literature, while some variables are included because of relevance for our research. We are not able to include the market volatility, number of competing ICOs, age of the founder and whether the institutional investor is a crypto-specific investor, even though these variables have significant influence in the research by Fisch & Momtaz (2020). The reason why we are not able to include these variables is partly due to the lack of time and partly due to limited access to proprietary information. The timeframe in which this thesis is written and the limited access to information, is indeed a limitation of our research scope. Moreover, not including the failure rate or exchange listing ICO-performance measurements used in (Howell et al., 2020) is also due to the limitation of time.

Therefore, future research should be conducted on a more extensive data sample with access to more reliable and comprehensive data. As prior literature states (Fisch & Momtaz, 2020), we expect more available cryptocurrency data as it becomes more standardized with time.

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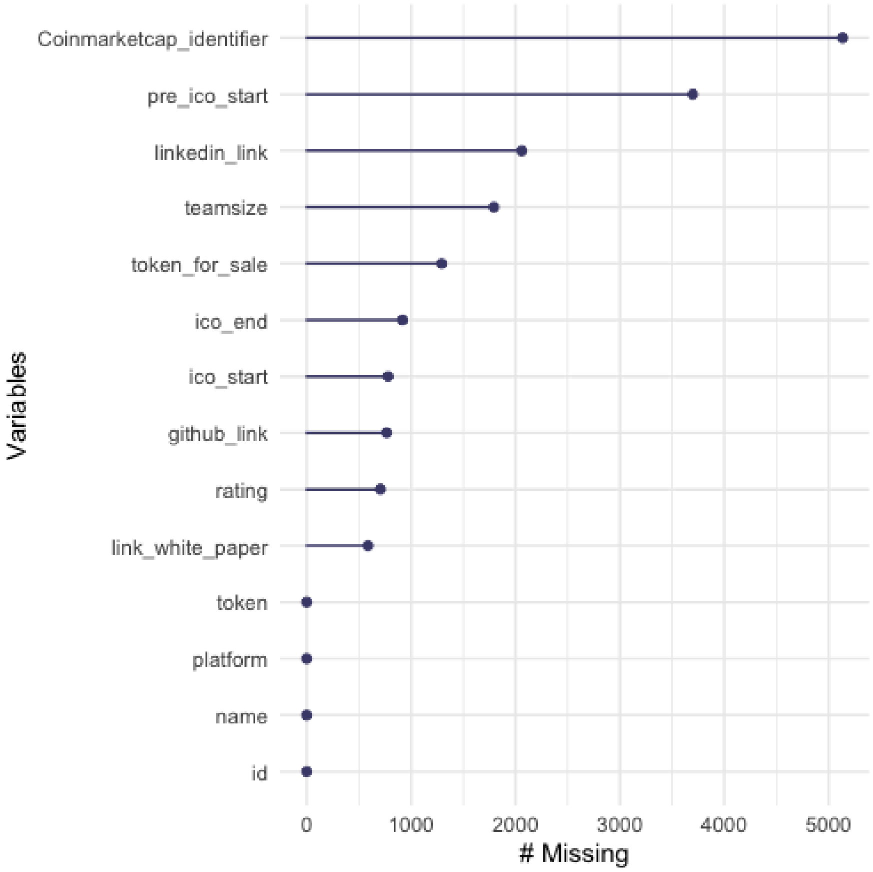
Appendices

A. Additional Tables and Figures

Figure A.1

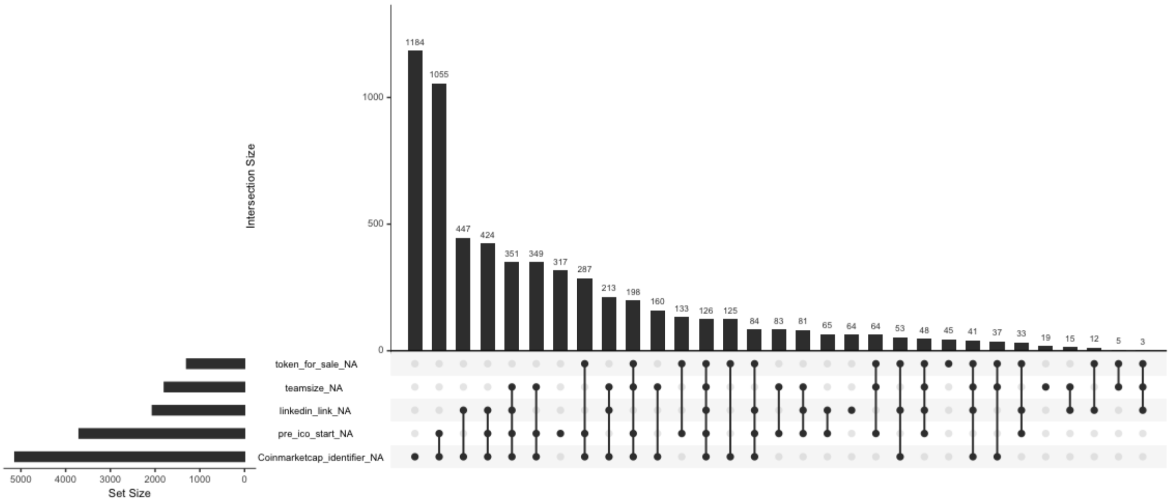
Missing Values In The Total TORD For The Variables Used



This figure displays the missing values in the TORD for the variables we use in our final model. In addition, the figure displays the missing values for the CoinMarketCap identifier in the TORD. The TORD consists of 6416 tokens in total. The figure illustrates that the CoinMarketCap identifier is the main missing data in the TORD, potentially due to tokens being delisted or never having been listed on an exchange. Thereafter pre-sale (pre_ico_start) is a variable that have missing data for circa 3800 ICOs.

Figure A.2

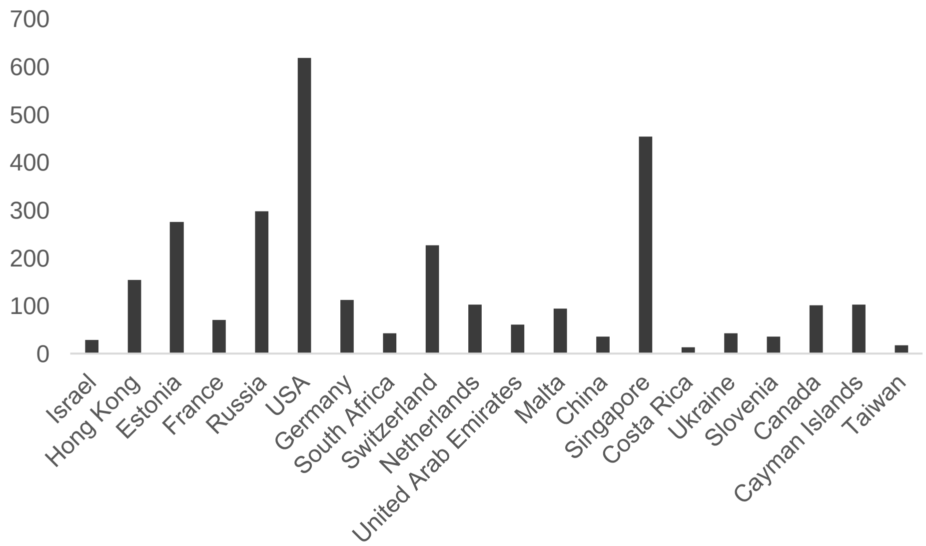
Relationship Between the Missing Values in the Total TORD



This figure displays the missing values for the variables used in our final model in the TORD, and the relationship between the different missing values. This figure indicates which missing values were removed in the first round of sample reduction and how these correlates with each other. For example, the figure illustrates that 1184 ICOs that are missing a CoinMarketCap identifier also have another missing variable. Furthermore, there are 1055 missing values for both pre-sale and CoinMarketCap identifiers for the same ICOs. Moreover, 447 of ICOs miss both the LinkedIn link and the CoinMarketCap identifier.

Figure A.3

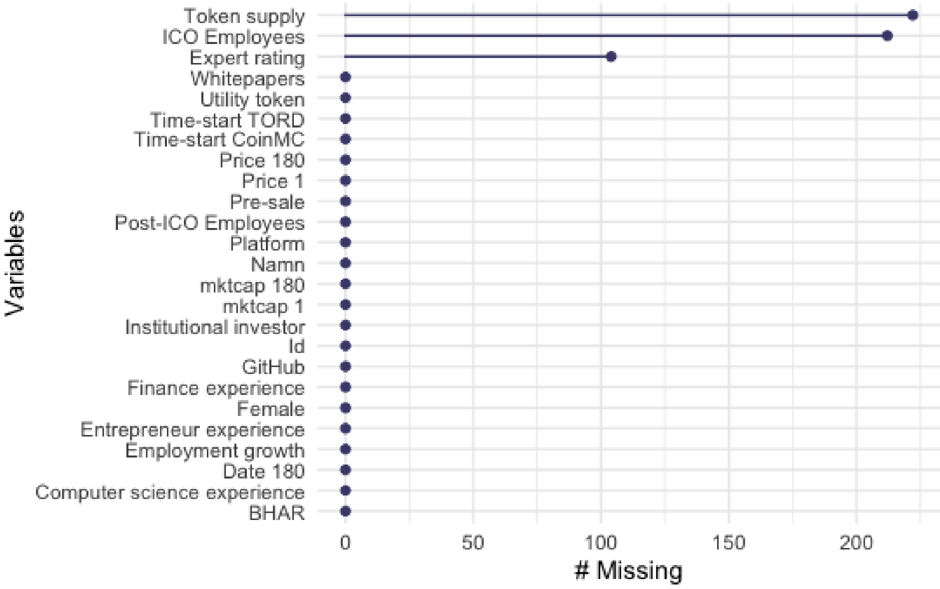
Relationship Between Missing CoinMarketCap Identifier and Issuer Country



This figure displays the relationship between missing CoinMarketCap identifiers and issuer country in the total TORD, consisting of 6416 tokens. The figure illustrates that the issuer countries that are missing most CoinMarketCap identifiers are USA and Singapore. Observing our sample in Figure A.6 one can see that the issuer countries that we have the most number of tokens from in our sample are USA and Singapore. This implies that our sample is not skewed due to the high rate of missing CoinMarketCap identifiers for tokens issued in the USA or Singapore.

Figure A.4

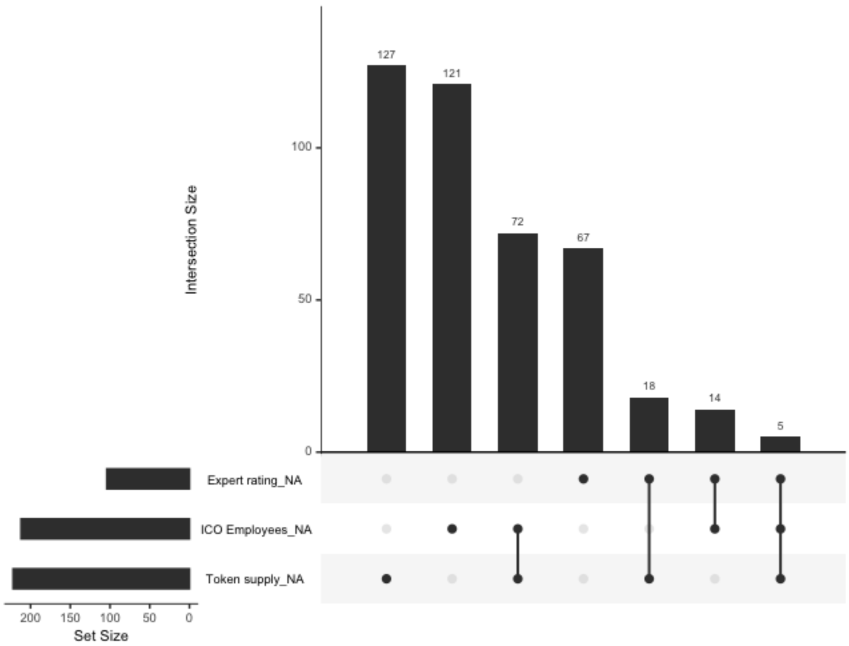
Missing Values in Our Total Final Sample



This figure displays the missing values and their distribution in our final sample consisting of 853 ICOs. In our final sample the only variables that have missing values are token supply, old employees and expert rating. These missing values we have filled with the sample's median. All other variables displayed in Figure A1 has been removed from our sample in order to fill as few values as possible with the median.

Figure A.5

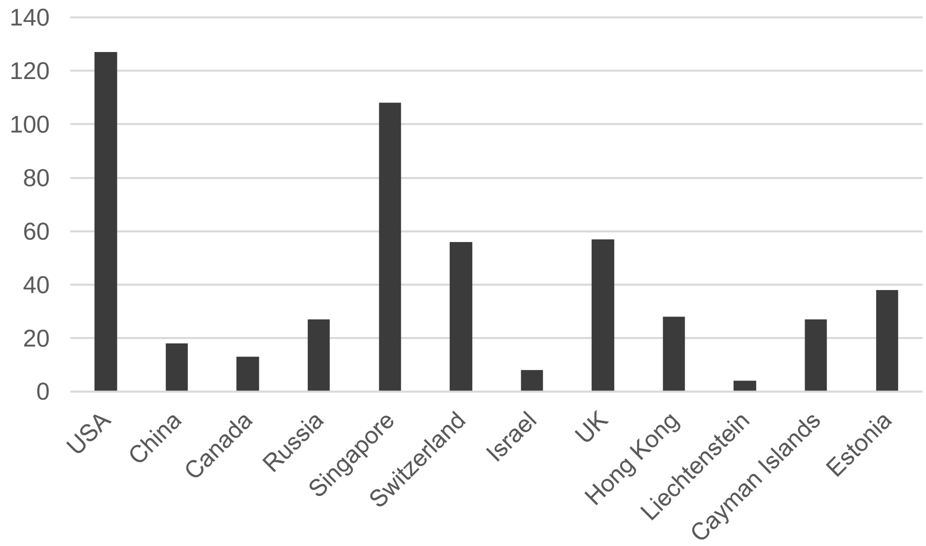
Relationship Between the Missing Values in Our Total Final Sample



This figure shows the missing values and their distribution in the final sample. The final sample is 853 ICOs and through this graph one can see that 126 ICOs with missing token supply are also missing other values, furthermore that 121 ICOs with missing number of employees during the ICO.

Figure A.6

Number of Issued Tokens per Issuer Country



This figure displays the main issuer countries in our final sample. The largest number of ICOs in our final sample are issued in the USA and Singapore.

Table A.1

Relationship Between Issuer Country and ICO Performance

	Dependent variable:			
	BHAR	Employment during ICO	Post-ICO Employment	Employment growth
	(1)	(2)	(3)	(4)
USA	-0.011	-0.100**	0.096*	0.059
	(0.293)	(0.051)	(0.056)	(0.053)
China	-0.014	-0.459***	-0.065	-0.145
	(0.711)	(0.123)	(0.136)	(0.128)
Russia	-0.009	-0.191*	-0.046	0.018
	(0.586)	(0.101)	(0.112)	(0.105)
Switzerland	0.001	-0.009	0.153*	0.056
	(0.417)	(0.072)	(0.080)	(0.075)
UK	1.513***	-0.047	-0.096	0.095
	(0.414)	(0.072)	(0.079)	(0.074)
Estonia	-0.010	0.139	-0.090	-0.047
	(0.498)	(0.086)	(0.095)	(0.090)
Observations	852	852	852	852
R^2	0.016	0.027	0.012	0.006

This table presents the relationship between the issuer country and ICO performance. The dependent variables are the BHAR, employment during ICO, post-ICO employment and employment growth, and the six most common issuer countries are the independent variables. Note that only the issuer countries which have a significant impact on the ICO performance is displayed in this figure. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05; ***p<0.01

Table A.2

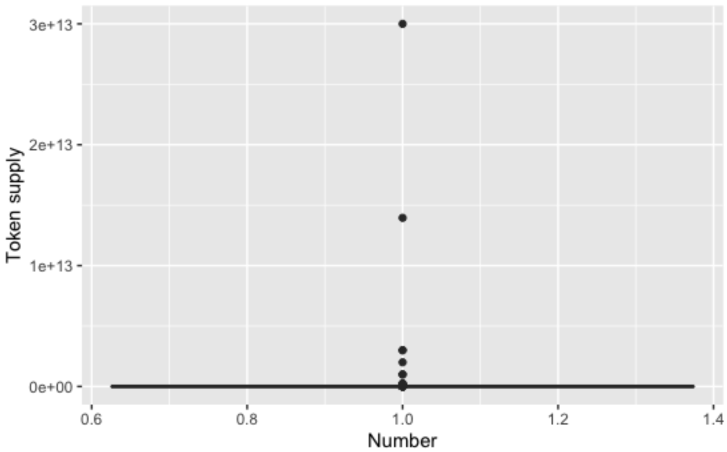
Funding Amount in Relationship to Post-ICO Performance

	Dependent variable:		
	Funding amount		
	(1)	(3)	(4)
BHAR	-0.037***		
	(0.007)		
Post-ICO Employees		0.155***	
		(0.035)	
Employee growth			0.123***
			(0.036)
Observations	853	853	853
R^2	0.035	0.022	0.013

This table presents the results from the OLS regressions using the founding amount as the dependent variable and the BHAR, post-ICO employment and employment growth as independent variables. The table shows that there is a negative relationship between the funding amount and the BHAR. Indicating that if the BHAR is higher, the ICO raised a smaller funding amount. Meanwhile, the post-ICO employment shows the opposite, indicating that when an ICO has a 1% larger funding amount the venture has 24,4% more employees, therefore a positive relationship. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05; ***p<0.01

Figure A.7

Extreme outliers in the Token Supply



This figure displays a boxplot illustrating the distribution of the token supply variable. The figure shows that our sample has two extreme outliers.

Table A.3

Funding Amount in Relationship to Institutional Investors

	Dependent variable:
	Funding
Institutional investor	0.331^{*}
	(0.199)
Generalized residual	YES^{***}
	(0.033)
Whitepapers	-0.002
	(0.071)
Pre-sale	-0.018
	(0.052)
Platform	-0.002
	(0.042)
Token supply (log)	0.022
	(0.023)
Expert rating (log)	0.289
	(0.225)
Utility token	0.053
	(0.065)
Observations	853
R^2	0.044

This table presents the results from a 2SLS regression between funding and institutional investors, using a rCF approach. The first stage is the regression from table A.1 ($INST_i = \Omega_i^{(s)}\delta + \xi_i$). The second stage is the funding dependent on a vector of issuer characteristics. We do not include the human capital characteristics from Howell et al. (2020) definition, but instead only present the variables that are in line with Fisch & Momtaz, (2020) and the variable for whitepapers to be able to get a picture of how the funding looks like in relation to the issuer characteristics. The regression shows that funding is significally positively related to institutional investor backing. This implies that institutional backing result in a higher funding amount when controlling on a vector of issuer characteristics. All models include robust standard errors. All variables are defined in Table 1. Statistical significance is attributed based on p-values as follows: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

B. Robustness of Empirical Results

Table B.1

Institutional Investor Backing and ICO-performance - Inverse mills ratio

	Dependent variable:								
	Institutional investor	BHAR		Post-ICO Employees		Employment during ICO		Employment growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Institutional investor			11.102**		2.399***		0.319		1.791**
			(4.942)		(0.731)		(0.401)		(0.819)
Inverse mills ratio			YES		YES**		YES		YES*
			(+)		(+)		(+)		(+)
Whitepapers	-0.082	0.077	0.281	-0.137**	-0.101*	0.005	0.010	-0.091	-0.065
	(0.280)	(0.366)	(0.376)	(0.054)	(0.056)	(0.030)	(0.031)	(0.061)	(0.062)
Pre-sale	-0.738***	0.256	1.671**	-0.069**	0.222**	0.047**	0.086	-0.119***	0.096
	(0.187)	(0.227)	(0.664)	(0.034)	(0.098)	(0.018)	(0.054)	(0.038)	(0.110)
Platform	-0.342**	0.168	0.875**	0.005	0.148***	0.037**	0.056*	-0.023	0.082
	(0.163)	(0.209)	(0.375)	(0.031)	(0.055)	(0.017)	(0.030)	(0.035)	(0.062)
Token supply (log)	0.107	0.008	-0.205	-0.009	-0.053**	0.026***	0.020*	-0.041**	-0.073***
	(0.092)	(0.116)	(0.149)	(0.017)	(0.022)	(0.009)	(0.012)	(0.019)	(0.025)
Expert rating (log)	0.490	-0.380	-1.357	0.753***	0.553***	0.301***	0.274***	0.437**	0.289
	(0.908)	(1.152)	(1.228)	(0.171)	(0.182)	(0.093)	(0.100)	(0.191)	(0.204)
Utility token	-0.187	0.073	0.425	-0.020	0.054	0.016	0.026	-0.066	-0.011
	(0.257)	(0.339)	(0.372)	(0.050)	(0.055)	(0.027)	(0.030)	(0.056)	(0.062)
Entrepreneur experience	0.702***	-0.096	-1.561**	0.287***	-0.013	0.032*	-0.008	0.199***	-0.023
	(0.165)	(0.216)	(0.681)	(0.032)	(0.101)	(0.017)	(0.055)	(0.036)	(0.113)
Computer science experience	0.566***	-0.096	-1.337**	0.248***	-0.004	0.026	-0.007	0.168***	-0.018
	(0.182)	(0.248)	(0.601)	(0.037)	(0.089)	(0.020)	(0.049)	(0.041)	(0.100)
Finance experience	0.026	-0.087	-0.134	0.207***	0.199***	0.009	0.007	0.113**	0.107**
	(0.236)	(0.310)	(0.310)	(0.046)	(0.046)	(0.025)	(0.025)	(0.051)	(0.051)
Female	0.487***	-0.162	-1.136**	0.465***	0.266***	0.033*	0.006	0.334***	0.187**
	(0.166)	(0.213)	(0.479)	(0.032)	(0.071)	(0.017)	(0.039)	(0.035)	(0.079)
Observations	853	853	853	853	853	853	853	853	853
R^2		0.004	0.011	0.394	0.404	0.072	0.073	0.204	0.210

This table presents the 2SLS results with the inverse mills ratio approach. Column (1) presents the selection model ($INST_i=\Omega_i^{(s)}\delta+\xi_i$) which estimates the institutional investor variable by a vector of all the control variables included in the paper. Column (2), (4), (6) & (8) presents the control models which regresses the dependent variables on a vector of all the control variables with the institutional investor variable excluded. Column (3), (5), (7) & (9) regresses the performance models in which the *inverse mills ratio* replaces the *GENRESi* variable to employ a robustness test of the rCF. The equation for the inverse mills ratio is the following: $IMR_i=\frac{\phi(\frac{\Omega_i^{(s)}\delta}{\sigma_\xi})}{\Phi(\frac{\Omega_i^{(s)}\delta}{\sigma_\xi})}$. All variables are defined in Table 1. Statistical significance is attributed based on p-values as follows: *p<0.1; **p<0.05;***p<0.01.