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What determines success in initial coin offerings?

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ABSTRACT

We analyse the determinants of success for 630 ICOs undertaken from August 2015 up until the end of December 2017, a period in which the market for ICOs grew to an unprecented level. We find evidence that ICOs are more successful in raising funding when they disclose more information to investors (i.e. have a higher profile rating), have a higher quality rating by cryptocurrency experts, have a pre-ICO GitHub repository, organise a presale, refrain from offering bonus schemes, have shorter planned token sale durations and have a larger project team. ICOs that disclose more information to investors and that have a higher quality rating at the time of the campaign show stronger ex-post performance. Longer-term project success is positively impacted by having a pre-ICO GitHub repository, a shorter planned token sale duration and having a larger project team at the time of the ICO, although these results depend on the ex-post success measure used. We conclude that for entrepreneurs it is important to make an ICO as transparent as possible and that profile and expert ratings are a valuable means to overcome the information asymmetry problems associated with token sales.

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1. Introduction

Initial Coin Offerings (ICOs) have become an increasingly popular way to raise capital for blockchain technology startups. In an ICO, entrepreneurs raise money for their venture by selling newly created cryptocurrency tokens to investors in exchange for fiat currency such as US dollars or cryptocurrencies such as Ethereum or Bitcoin (Chohan 2020; Kastelein 2017). At the time of the ICO, the project is mostly at the idea stage and the actual launch of the product or service is expected within one to two years after the ICO (EY 2017). The cryptocurrency tokens typically act as a digital medium of exchange to access the firm's digital platform and services. After completing the ICO, the tokens may be traded on an online exchange and increase in value with the success of the project. One advantage for entrepreneurs is that ICOs allow them to raise capital by selling tokens rather than shares and therefore do not require them to give up ownership and control rights to investors as would be the case with venture capital or equity-based crowdfunding (Schwienbacher 2019).

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The total amount of funding through ICOs in 2017 equalled 5.38 USD billion, surpassing early-stage venture capital investments in blockchain startups (Sunnarborg 2017) and 12 USD billion in the 16 months since January 2017 (Benedetti and Kostovetsky 2018). Some blockchain startups have been able to raise capital via token sales at record speed, largely because of investors' fear of missing out (referred to as FOMO). For example, the company Gnosis was able to raise 12 USD million in less than 10 minutes (Cointelegraph 2017). At the same time, the number of blockchain startups reaching their maximum fundraising goal has declined since the last quarter of 2017 and regulators are pointing out the risks associated with largely unregulated ICOs such as fraud, exaggeration of expected returns and lack of transparency (EY 2017; SEC 2017).

In their review of new developments in venture capital funding, Harrison and Mason (2019) mention ICOs to be the most recent player in the market for risk capital. They discuss the growth of the market and mention four important elements of ICOs, i.e. (i) reduction in the cost of capital, (ii) open-source product development, (iii) peer-to-peer platforms, and (iv) the creation of secondary markets. Harrison and Mason (2019) also mention the collapse of the market in the third quarter of 2018 as an indication that the rise of ICOs may have been a bubble. However, they argue that ICOs cannot be marked as a scam and that, with appropriate regulation, ICOs can become a viable disruptive technology, representing a fertile avenue for further research.

In this paper, we aim to understand the determinants of both funding and ex-post success of ICOs launched in the period before the collapse of the market. In the first part of our analysis, we focus on funding success and question why some projects succeed in raising funding in ICOs and get their tokens listed on CoinMarketCap, a leading website for tracking exchange-traded cryptocurrencies, whereas others do not.[1] Our sample includes both uncapped and capped ICOs. In an uncapped ICO, the token supply is not limited or the token price is not known beforehand. This contrasts with the vast majority of capped ICOs in which the company sells a limited supply of tokens at a fixed price. In a capped ICO the company may set two funding goals: a minimum fundraising goal (softcap) as well as a maximum fundraising goal (hardcap). The company only keeps the money it has raised in case the amount raised exceeds the pre-set softcap ("all-or-nothing"). Once the softcap has been reached the company keeps all the money it raises even if the hardcap has not been reached ("keep–it-all"). In our analyses, we use several dependent variables to measure funding success in order to reflect the different ways ICOs can be structured: a binary variable indicating whether the ICO reaches its softcap (if any), the amount of money raised as a percentage of the hardcap (only in capped ICOs), the log of the amount of money raised in the ICO, and a binary variable indicating whether the ICO is listed on CoinMarketCap. In our analysis, we focus on the period in which the ICO market grew to unprecedented volume because we are interested in understanding the mechanics of the build-up of this new market. We employ a large sample of 630 capped and uncapped ICOs from August 2015 until December 2017.

In the second part of our analysis, we look beyond funding success and also investigate whether the project is successful afterwards or has ended up on what Varshneya (2018) calls the "digital graveyard". We focus on 472 projects that successfully raised money and investigate whether these projects have survived up to November 2019. We use five measures of ex-post success: whether the project's website is still online in November 2019, the number of Tweets per week since the ICO commenced, whether the project has recently been active on Twitter, whether the project has recently updated its repositories on the software development platform GitHub, and whether the ICO ended up on the digital graveyard or not in November 2019 (i.e., traded below 10% of its original ICO price or was no longer tracked on CoinMarketCap).

Our results show that ICOs with a higher profile and expert rating are more successful in raising funds and perform better ex-post. We find evidence that having a pre-ICO GitHub repository, organising a presale for early investors, a shorter planned token sale duration, not having a bonus scheme, and having a larger project team is positively associated to fundraising success. Longer-term project success is positively impacted by having a pre-ICO GitHub repository, a shorter planned token sale duration and having a larger project team at the time of the ICO, although results depend on the ex-post success measure used.

Our paper adds to the literature on entrepreneurial finance and the emerging literature on ICOs. Existing studies on ICOs model the choice between ICO and venture capital funding (Catalini and Gans 2018; Chod and Lyandres 2018), investigate the need for legislation of ICOs (Kaal 2018), the geography of ICOs (Huang, Meoli, and Vismara 2019), the returns, liquidity and trading volume of exchange-traded ICOs (Howell, Niessner, and Yermack 2018; Benedetti and Kostovetsky 2018; Lyandres, Palazzo, and Rabetti 2019), and reasons for entrepreneurs to launch peer-to-peer platforms (Li and Mann 2018). We are aware of several other (working) papers on the determinants of funding success of ICOs. First, Adhami, Giudici, and Martinazzi (2018) investigate 253 ICOs from 2014 until August 2017 of which 81 percent reached the minimum funding goal. They find that ICOs are more likely to reach the funding goal in cases where their programming code is (partially) available in an online GitHub repository (measured after the ICO), when the company has presold tokens to early-stage investors and when tokens come with the right to access services or in some cases to a share in the profits. Second, Fisch (2019) examines 423 ICOs in 2016–2018. He finds that the dollar amount raised in the ICO is positively impacted by technical white papers and good quality source code, where the latter is measured by the number of GitHub defect fixes. Third, Amsden and Schweizer (2019) look at a sample of 1,009 ICOs (573 of which have data on funding amounts) from 2015 until March 2018 and use the listing on CoinMarketCap as their main success measure. They report that venture uncertainty is negatively correlated with success while venture quality has a positive impact on ICO success.

We contribute to the recent literature on ICOs and complement previous findings in four ways. First, we investigate a number of previously unexplored determinants (most importantly, expert and profile ratings and *planned* ICO duration in days). Second, we use a richer set of fundraising success measures that distinguish between capped versus uncapped ICOs and take into account the softcap and hardcap fundraising goals. Also, we use a funding success measure that captures whether the ICO is trading on an exchange recognized by CoinMarketCap, a tracking website for exchange-traded cryptocurrencies. Adhami, Giudici, and Martinazzi (2018) only analyse whether the minimum funding goal has been reached and Fisch (2019) uses the log of the amount raised as the dependent variable. Amsden and Schweizer (2019) use token tradability on an exchange tracked by CoinMarketCap as their key measure of success. Third, we make use of the largest slice of the ICO universe for which data is available during our sample period. We use eleven ICO databases[2] to obtain this data, as no single database covers the full ICO universe. One issue that all ICO studies face is that many of the ICOs that end up being unsuccessful delete their data. These ICOs are thus less likely to be included in the analysis. However, we only miss out on a few unsuccessful ICOs. Our sample includes 630 out of the 682 ICOs listed on ICObench, a respected rating website for ICOs, during our sample period. This allows us to paint a more comprehensive picture of the determinants of ICO success during this period. Fourth, we extend the existing papers on ICO funding success by adding an analysis of ex-post success of ICOs for a period of almost two years at least, which accounts for the most recent developments in the ICO market. This adds to the findings of Amsden and Schweizer (2019) who examine a smaller sample of 134 ICOs that are tracked by CoinMarketCap using a dummy measure of ex-post ICO success indicating one if the token price at 30, 180, or 360 days after the ICO is above the original ICO price. We evaluate token performance during a time window of nearly two years at the minimum and make use of five success measures to assess the survivability of the projects.

The remainder of this paper is structured as follows. Section 2 derives our hypotheses. We describe our sample in Section 3. Section 4 presents our results. We conclude in Section 5.

2. Hypotheses development

Information asymmetry is one important barrier to the financing of early-stage ventures (Chod and Lyandres 2018). At the time of the ICO, there are no compulsory or audited disclosures and the project is mostly at the idea stage with the actual launch of the product or service only expected within one to two years after the ICO (EY 2017). Moreover, there is no or little regulation and investor protection. In theory, this context would impair successful fundraising by blockchain technology startups.

The ex-ante information problem of hidden information or adverse selection (Akerlof 1970) cannot be addressed by high-quality ICOs simply stating that they are of the high-quality type. Also, a low-quality ICO could (falsely) claim to be of the high-quality type and therefore investors would ignore this "cheap talk". Investors use several information sources to assess the quality of the token sale such as GitHub, Twitter, Telegram/Slack/Discord, Bitcoinwiki, Facebook, Bitcointalk, whitepapers, videos, and LinkedIn. We hypothesize that voluntary disclosure acts as a quality signal. Project teams of high-quality projects are more willing to disclose information whereas project teams of poor quality projects are less willing to share information with potential investors, especially when they face penalties if the disclosure proves to be fraudulent ex-post (e.g., see the theoretical model of Hughes 1986). These higher-quality projects are then also expected to perform better in the longer-run. We hypothesize:

Hypothesis 1A: More extensive disclosure (i.e., a higher profile rating) has a positive influence on fundraising success

Hypothesis 1B: More extensive disclosure (i.e., a higher profile rating) has a positive influence on subsequent project success

At the same time, projects might be hesitant to share technical proprietary information in whitepapers or in a public GitHub repository with a wider circle of investors because the product or service is still under development and intellectual property rights by patents and/or trademarks are not (yet) in place. In addition, the technical information in whitepapers seems difficult to comprehend by most investors in ICOs (Samieifar and Baur 2020) and most investors do not have the time and expertise to conduct due diligence of the project themselves. One solution to this problem is to make use of ratings by experts. A respected rating website in the crypto-sphere, consisting of experts who voluntarily review ICOs, is ICObench. To become an expert one must show a thorough knowledge of cryptocurrencies and its underlying market dynamics. Reviewers obtain no compensation.[3] We expect that highly rated ICOs are more likely to be successful in raising funds and in the period after the ICO. Therefore, we hypothesise that:

Hypothesis 2A: Higher ratings by expert reviewers have a positive influence on fundraising success

Hypothesis 2B: Higher ratings by expert reviewers have a positive influence on subsequent project success

Another way to mitigate the adverse selection problem is signalling (Spence 1973). In the case of signalling the project deliberately makes use of positive and observable indicators of otherwise not directly observable qualities in an attempt to mitigate the ex-ante information problem with investors (Spence 2002). In order to be effective, a signal needs to be costly and correlate strongly with the quality it plans to indicate. High-quality ICOs are better able to absorb the higher costs of signalling. Low-quality projects will not imitate the signal of high-quality projects because they are not able or willing to bear the high costs associated with the signal. The benefits of being correctly identified as a high-quality ICO would outweigh the high costs only in case the project is truly of the high-quality type. The decision to post the programming code underlying the project on a software development platform and repository GitHub can be seen as such a signal. It would allow experts to review the programming code and information about the technical side of the project before the ICO and collaborate on further improvements in the period after the ICO. Only companies that are confident about the technical side of their project would subject it to expert scrutiny on GitHub before the ICO. These companies are expected to be more successful in raising funds as well as showing superior long-term performance afterwards. We hypothesize:

Hypothesis 3A: Posting programming code or technical information on software repository GitHub before the ICO has a positive influence on fundraising success

Hypothesis 3B: Posting programming code or technical information on software repository GitHub before the ICO has a positive impact on subsequent project success

The distribution of tokens to insiders may be another important signal to investors. In ICOs, the percentage of tokens owned by the insiders after the ICO is known at the time of the ICO. These exchange-traded tokens can be sold in the future at a higher price in case the project is successful and needs to raise fresh capital. This signals that project developers are confident about the future success of the project and refrain from raising as much capital as possible from investors at the time of the ICO. The percentage of tokens held by insiders may also mitigate a potential ex-post information or moral hazard problem. If insiders continue to own a significant percentage of the tokens they have a strong incentive to work hard towards a successful launch the blockchain project.

Hypothesis 4A: A higher percentage of tokens retained by insiders positively impacts fundraising success

Hypothesis 4B: A higher percentage of tokens retained by insiders positively impacts subsequent project success

An ICO can take place in multiple stages, i.e. a pre-ICO can be launched to test market demand and estimate a price for the token. Before opening the ICO to the public, early-bird investors are typically able to obtain bonuses (e.g. deep discounts for early investors without lockups or vesting periods) to encourage early participation and to generate momentum. Typically there is a higher minimum investment amount compared to the public sale that follows afterwards. The ICO presale tends to be smaller than the public sale of the ICO and is intended to show to the public that the project team was able to have a pool of (befriended) cornerstone investors willing to invest in the project already.

Hypothesis 5: ICOs preceded by a presale are more likely to successfully raise funds in the public phase of the ICO

The public ICO sale follows suit, is open for everyone to invest in, and often has a lower minimum investment amount compared to the presale. Early investors in public token sales can also qualify for bonuses and price discounts albeit lower compared to the presale. This creates an incentive for investors to invest as soon as possible out of fear of missing out. However, having to make use of bonus schemes in the public phase of the ICO may also signal that the project team is struggling to attract sufficient interest in the presale (if organized) or in the ICO itself and that, despite the bullish market for ICOs in our sample period, it needs to resort to bonuses and price discounts to attract public investors. Moreover, potential investors may be afraid that too many bonus participants can engage in flipping and sell the tokens at a profit (at ICO price) once the tokens launch on a secondary market, driving the price down. We hypothesize that the use of bonus schemes in the public part of the ICO has a negative effect:

Hypothesis 6: The use of bonus schemes in the public phase of the ICO negatively impacts fundraising success

At the launch of the ICO, the project team announces the number of days the campaign will accept funding. In the context of reward-based crowdfunding, Mollick (2014) reports that campaigns with a longer duration have a lower probability of reaching their funding goals. Planning on a longer duration may signal a lack of confidence in the project to potential investors (Mollick 2014). We, therefore, hypothesize that a longer *planned* duration of the ICO campaign at the time of its launch negatively impacts fundraising success.

Hypothesis 7: Longer planned campaign durations have a negative influence on fundraising success

Investors may appreciate larger project teams, as it may show that a larger number of people are willing to work on bringing the project to fruition, speeding up the time to the actual launch of the blockchain project. Ahlers, Cumming, Gunther and Schweizer (2015) show that human capital (proxied by the number of board members) is positively related to funding success on one of the first crowdinvestment platforms, the Australian Small Scale Offerings Board. In addition, a larger project team implies a larger network of contacts it can mobilize to promote the ICO and assist in the project´s future development in the post-ICO period. We hypothesize:

Hypothesis 8A: Having a larger project team positively impacts fundraising success

Hypothesis 8B: Having a larger project team positively impacts subsequent project success

3. Data and methods

We start with an initial dataset consisting of 682 ICOs from ICObench and other sources during the period August 2015 until December 2017.[4] We stop in December 2017 in order to measure success as survival for a period of nearly two years or longer. Because information is widely dispersed on the Internet and most databases often include only partial information, we identify these ICOs from eleven databases.[5] Out of the available databases, ICObench provides the most thorough and highest quality information on ICO campaigns and therefore serves as the core of our sample. By using the Application Programming Interface (API), it is possible to draw information from the database directly. Even though we consider ICObench the most comprehensive database, it still lacks key information which we manually supplemented with data from other databases, websites, forum threads and whitepapers.

For 52 out of 682 ICOs, it is not possible to find relevant information on the Internet, because websites, forum posts and Twitter accounts have been deleted or the crowdsale never took place. In cases where insufficient data is available online, we exclude the ICO from the dataset. In a handful of cases where we could not obtain the amounts of capital raised directly from ICObench or other sources, we have analysed the transactions on the blockchain during the ICO period to calculate the funding amount ourselves.[6] This resulted in a sample consisting of 630 ICOs.

In our analyses we use four measures of funding success as our dependent variables, reflecting the different ways in which ICOs are structured. Table 1 shows the variable

Table 1. Variable definitions.

Variable	Definition	Data source
Dependent variables:		
Funding success:		
Softcap hit (dummy)	Dummy indicating one if the softcap is reached, zero otherwise	ICObench*
Funding percentage (%)	Funding raised as percentage of hardcap	ICObench*
Funding raised ($ million)	Funding raised in millions of US dollars	ICObench*
Token tradability (dummy)	Dummy indicating one if the ICO is traded on an online exchange tracked by CoinMarketCap, zero otherwise	CoinMarketCap
Ex-post success:		
Website online (dummy)	Dummy indicating one if the project's website is online in November 2019, zero otherwise. Only ICOs that successfully raised more than $50 k are taken into account.	Google
Tweets per week (#)	Number of Tweets per week measured during the period between the start of the ICO and November 2019. Only ICOs that successfully raised more than $50 k are taken into account.	Twitter
Twitter activity (dummy)	Dummy indicating one if there are any Tweets from the project team in the period September until November 2019, zero otherwise. Only ICOs that successfully raised more than $50 k are taken into account.	Twitter
GitHub activity (dummy)	Dummy indicating one if there are any contributions to any of the project's GitHub repositories in the period September until November 2019, zero otherwise. Only ICOs that successfully raised more than $50 k are taken into account.	GitHub
Graveyard (dummy)	Dummy indicating one if the price in November 2019 was below 10% of the price at which the token was originally sold in the token sale or if the token was delisted from CoinMarketCap. Only ICOs that successfully raised more than $50 k are taken into account.	CoinMarketCap
Independent variables		
Expert rating (from 1–5)	The equally weighted average of ratings on product quality, vision quality and team quality by expert reviewers. Ranges from one to five.	ICObench*
Profile rating (from 0–5)	Profile rating of the ICO, based on a computer algorithm and incorporating 31 distinct elements. Ranges from zero to five. This rating includes whether the project: (i) is covered on GitHub, Twitter, Telegram/Slack/Discord, Reddit, Bitcoinwiki, Facebook and Bitcointalk ANN thread; (ii) has an informative whitepaper and/or video available, a minimum viable product or prototype is mentioned, and milestones are listed; (iii) discloses the full names, LinkedIn profiles, photos of the project team, and/or; (iv) discloses its ICO start date, ICO end date, token ticker, platform, accepted currencies, token price, bonus schemes, country of registration, and any hardcap or softcaps.	ICObench*
GitHub_preICO (dummy)	Dummy indicating one if the project has one or more GitHub repositories at the time of the ICO, zero otherwise	GitHub
Insider token retention (%)	Percentage of tokens retained by the project team	ICObench*
Presale (dummy)	Dummy indicating one if there is a presale of tokens to early bird investors, zero otherwise	ICObench*
Bonus scheme (dummy)	Dummy indicating one if there is a bonus scheme (discounts and/or free tokens) in the public phase of the ICO, zero otherwise	ICObench*

(*Continued*)

Table 1. (Continued).

Variable	Definition	Data source
Duration (# days)	Number of *planned* days for the ICO campaign at the time of its launch	ICObench*
Team members (#)	Number of members of the project team	ICObench*
Control variables		
Softcap ($ million)	Softcap target amount in millions of US dollars	ICObench*
Hardcap ($ million)	Hardcap target amount in millions of US dollars	ICObench*
Uncapped ICO (dummy)	Dummy indicating one if the ICO is uncapped, zero otherwise	ICObench*
Accepted currencies (#)	Number of accepted cryptocurrencies that are accepted as payment for the tokens	ICObench*
Fiat currency (dummy)	Dummy indicating one if a fiat currency (e.g. US dollars) can be used as payment for the tokens, zero otherwise	ICObench*
Ethereum platform (dummy)	Dummy indicating one if the project is (partly) based on the Ethereum blockchain, zero otherwise	ICObench*
Token price ($ cents)	Token price in US dollar cents	ICObench*
Total tokens (in millions)	Total number of tokens after ICO in millions (circulating and retained)	ICObench*
Ethereum return (%)	Return on Ethereum during a 30-day window preceding the ICO launch date	CoinMarketCap
Ethereum volatility (%)	Standard deviation of the daily return on Ethereum during a 30-day window preceding the ICO launch date	CoinMarketCap
ICO volume (#)	Number of ICOs in the month in which the ICO is launched	CoinMarketCap

Note: * In case data was missing on ICObench, it is complemented by using information from additional sources such as: www.tokendata.io, www.icotracker.net, www.cryptocompare.com/ico, www.smithandcrown.com/icos, https://elementus.io/token-sales-history, www.icomarketdata.com, www.icodata.io, www.coindesk.com/ico-tracker/, www.icobench.com/ico, www.coinschedule.com, www.ico-list.com, www.icostats.com. Additionally, we consulted the whitepaper, website, Bitcointalk forum thread, Telegram, Twitter and Facebook of the ICO to complement missing data.

definitions. Table 2 provides an overview of the ICO distribution (country of origin, project category and blockchain used) in our sample. Table 3 presents the descriptive statistics. We measure funding success with a dummy variable indicating whether the softcap (i.e. the minimum funding goal) has been reached, the amount of capital raised as a percentage of the hardcap (i.e. the maximum funding goal), the log of the amount of capital raised, and a dummy variable indicating whether the ICO was admitted to trading on an online exchange that is tracked by CoinMarketCap. Table 3 shows that 185 ICOs make use of a softcap (29% of the sample). The softcap averages 4.96 USD million and 85 ICOs with softcaps (46% of the sample with softcaps) manage to raise more capital than the minimum target amount. Our sample contains 575 capped ICOs (91.3% of the sample) and 55 uncapped ICOs (8.7% of the sample). The average hardcap is set at 56.5 USD million for the capped ICOs. On average, a capped ICO raises 34% of its hardcap. The average amount of capital raised amounts to 9.55 USD million with a minimum of zero and a maximum of 258 USD million. Cryptocurrencies frequently accepted as payment are Ethereum (in 533 ICOs, 85% of the sample), followed by Bitcoin (in 184 ICOs, 29% of the sample). Fiat currency is only accepted in 41 ICOs (6.5% of the sample). In our sample 163 ICOs accept multiple currencies as a means of payment for the tokens (26% of the sample). Half of the ICOs in our sample are admitted to trading on an online exchange tracked by CoinMarketCap.

We also use five dependent variables to measure the success of the project afterwards. We look at whether the website of the project is still online in November 2019, the Tweets from the project team per week in the period between the start of the ICO and November 2019, whether there have been any Tweets by the project team in the period September until November 2019, whether there have been any contributions on software repository GitHub during that same period and whether the ICO ended up on the

Table 2. Sample distribution.

Country			Category			Blockchain		
	Count	%		Count	%		Count	%
USA	121	19.2	Platform	166	26.3	Ethereum	533	84.6
Russia	85	13.5	Currency	100	15.8	Waves	39	6.2
UK	47	7.4	Business services	66	10.5	BitShares	5	0.8
Singapore	42	6.7	Entertainment	45	7.1	NEO	4	0.6
Switzerland	27	4.3	Investment	31	4.9	NEM	3	0.5
Canada	17	2.7	Software	31	4.9	Omni	3	0.5
Estonia	14	2.2	Banking	28	4.4	Counterparty	2	0.3
Australia	13	2.1	Casino & gambling	18	2.9	Litecoin	2	0.3
Germany	11	1.7	Internet	15	2.4	NXT	2	0.3
Hong Kong	11	1.7	Real estate	15	2.4	Ardor	1	0.2
Israel	11	1.7	Other	14	2.2	Electroneum	1	0.2
Netherlands	11	1.7	Media	11	1.7	Expanse	1	0.2
Slovenia	11	1.7	Health	9	1.4	Filecoin Network	1	0.2
China	8	1.3	Tourism	9	1.4	Maidsafe	1	0.2
Lithuania	8	1.3	Infrastructure	8	1.3	NEBL	1	0.2
France	7	1.1	Sports	8	1.3	Own	1	0.2
Japan	7	1.1	Communication	7	1.1	QRC	1	0.2
Spain	7	1.1	Education	7	1.1	Tendermint	1	0.2
Unknown	60	9.5	Retail	7	1.1	Unknown	26	4.1
Other	112	17.9	Other	35	5.7	Other	2	0.3
Total	**630**		**Total**	**630**		**Total**	**630**	

Table 3. Descriptive statistics.

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
Dependent variables:						
Funding success:						
Softcap hit (dummy)	185	0.46	0	0.5	0	1
Funding percentage (%)	575	34.24	14.14	39	0	100
Funding raised ($ million)	630	9.55	1.98	23.8	0	258
Token tradability (dummy)	630	0.5	1	0.5	0	1
Ex-post success:						
Website online (dummy)	472	0.79	1	0.41	0	1
Tweets per week (#)	429	8.91	5.61	12.16	0	119
Twitter activity (dummy)	429	0.51	1	0.50	0	1
GitHub activity (dummy)	309	0.46	0	0.50	0	1
Graveyard (dummy)	312	0.59	1	0.49	0	1
Independent variables:						
Quality rating (from 1–5)	311	3.39	3.47	0.93	1	5
Profile rating (from 0–5)	630	3.03	3	1.03	0.6	5
GitHub_preICO (dummy)	630	0.40	0	0.49	0	1
Insider token retention (%)	630	41.51	40	25.01	0	99
Presale (dummy)	630	0.38	0	0.49	0	1
Bonus scheme (dummy)	630	0.4	0	0.49	0	1
Duration (# days)	630	28.96	30	17.77	1	134
Team members (#)	630	9.58	8	7.54	1	57
Control variables:						
Softcap ($ million)	185	4.96	2	7.93	0.3	51
Hardcap ($ million)	575	56.53	20	347	0.02	7801
Uncapped ICO (dummy)	630	0.09	0	0.283	0	1
Accepted currencies (#)	630	1.59	1	1.36	1	13
Fiat currency (dummy)	630	0.07	0	0.25	0	1
Ethereum platform (dummy)	630	0.85	1	0.36	0	1
Token price ($ cents)	630	1,788.59	25.91	30,480.48	0.01	755,460
Total tokens (in millions)	630	20,229	100	337,554	0.01	8,000,000
Ethereum return (%)	630	24.32	6.41	51.96	−56.37	308.81
Ethereum volatility (%)	630	3.93	3.39	1.61	0	8.49
ICO volume (#)	630	89.35	102	40.86	1	140

Note: See Table 1 for data definitions.

graveyard (i.e. is trading below 10% of its original ICO price or is no longer tracked on CoinMarketCap in November 2019).[7] For the ex-post analysis, we only investigate 472 ICOs that successfully raised more than 50,000 USD during their campaign to ensure that our results are not driven by ICOs that have been unsuccessful at raising funds. This 50,000 USD threshold corresponds with the 25th percentile of the distribution of the funding amount raised in our sample of 630 ICOs. In other words, we have removed the bottom quartile of projects with the lowest amount of money raised from our ex-post analysis. About 80% of the project websites are still online in November 2019. The average (median) Tweet activity of the project team equals 8.9 (5.6) Tweets per week during the period between the end of the ICO and November 2019. There are 51% of projects with Twitter accounts that have recent Tweets in the period September-November 2019, and 46% projects with GitHub repositories at any point in time show recent activity on GitHub in that same period. A majority of ICOs that are initially tracked by CoinMarketCap (59%) ends up on the graveyard (e.g. trading at a price below 10% of the original ICO price or no longer being tracked by CoinMarketCap).

Our independent variables include the expert ratings and profile ratings on rating website ICObench, a dummy variable indicating whether the project created a GitHub repository before the ICO (retrieved via a Chrome extension), the percentage of tokens retained by insiders, a dummy variable whether a presale takes place before the public phase of the ICO, a dummy variable indicating whether a bonus scheme is used in the public token sale, the planned duration of the ICO in days and the number of project team members. Table 3 documents that the average (median) expert rating on ICObench equals 3.39 (3.47). The highest possible rating is five, corresponding to high-quality ICOs, whereas the lowest possible score is one, implying a weak investment opportunity. The expert rating consists of three elements: team, vision and product, and is available for 311 observations. The expert rating is based on the review of an average of 2.7 crypto-currency experts. The profile rating is available for all ICOs in the dataset and yields an average (median) of 3.03 (3). This rating is based on a computer algorithm and reflects the disclosure on ICObench for 31 distinct elements, such as the presence of GitHub, Twitter, and Facebook (for an extensive description consult Table 1). There are 253 projects with GitHub software repositories at the time of the ICO (40% of the sample). Insiders retain an average (median) of 42% (40%) of tokens. Presales happen in 241 cases (38.3% of the sample) and bonus schemes such as price discounts and free tokens are used in the public part of the ICO in 252 ICOs (40% of the sample). Table 3 shows that the average (median) duration of the ICO campaign is planned to be 29 days (30 days). The average (median) project team consists of 9.6 (8) members.

We include several control variables in our regressions. As there is no regulation concerning ICO structure, there are numerous possibilities for project developers in the design of the campaign that we need to control for. For example, the project developers can opt for a capped versus uncapped sale, make use of minimum fundraising goals (softcaps) and/or maximum fundraising goals (hardcaps) and accept payment in fiat currency and/or (multiple) digital currencies. The initial value and supply of the tokens are entirely at the discretion of the project developers, and often arbitrarily determined. In regressions using the funding percentage as the dependent variable, we control for the log of the hardcap (i.e., the maximum funding goal). In regressions using the other measures of funding success as dependent variables, we control for a dummy that indicates whether the ICO was uncapped or not. In uncapped ICOs, the investors are uncertain about how many tokens will be sold or about the cryptocurrency valuation. This could signal opportunistic behaviour or even greed on the part of the project developers as they sell as many tokens as investors want to buy (Buterin 2017). In contrast, in capped ICOs the maximum amount of funding is fixed. There are 55 uncapped ICOs (8.7% of the sample). When using the softcap hit as the dependent variable, we control for the log of the softcap (i.e. the minimum funding goal).

In addition, we control for the token price (excluding any bonuses and price discounts) and the log of the number of tokens created (i.e. the total of tokens that are sold and held by insiders). Investors might be more interested in tokens with lower prices and lower supply because they anticipate more upward potential for these lower-priced and scarce tokens. The average token price equals 17.9 USD but the median token price equals only 26 dollar cents. The average (median) number of tokens created amounts to more than 20 billion (100 million). The large difference between average and median values indicates the presence of outliers. Therefore, we log transform the variables token price and token supply. Furthermore, we include the number of accepted currencies for payment, a dummy variable indicating if paying with fiat currency was possible and a dummy variable related to whether the project is (partly) based on the Ethereum platform as control variables in our models.

Finally, we also control for market conditions. We include three additional control variables: (1) Ethereum return during a 30-day window preceding the ICO launch, (2) Ethereum volatility measured as the standard deviation of the daily return on Ethereum during a 30-day window preceding the ICO launch and (3) the number of ICOs during the month in which the ICO launch took place.

In the next section, we report our regression results. In the case of binary dependent variables, we make use of logistic regressions; in all other cases OLS regressions are used. In all tables, we report on the average and maximum Variance Inflation Factors (VIFs). None of our regression specifications has an average VIF exceeding three and only a handful has the maximum VIF slightly exceeding three. This is well below the threshold of ten that is commonly used to identify severe multicollinearity problems. We, therefore, conclude that multicollinearity is not a primary concern in our analysis.

4. Results

4.1. Determinants of funding success

In this section, we examine the determinants of funding success. We start with a univariate analysis presented in Table 4. Panel A shows the funding success measures split by the profile rating categories (ranging from 0 to 5). Panel B displays these success measures split by expert rating categories (ranging from 1 to 5). A clear pattern emerges showing that both higher profile and expert ratings are associated with more funding success. Table 4 also shows the difference in means between ICOs with a profile or expert rating above the median or below the median. ICOs with an above-median profile and expert rating are significantly more successful in reaching the softcap and raise more capital (both expressed as a percentage of the hardcap as well as the dollar amount) compared to ICOs with below-median profile or expert ratings. ICOs with an above-median profile and expert ratings are also more likely to have their tokens listed on CoinMarketCap than ICOs with a below-median score on these ratings.

Next, we conduct multivariate regression analyses that include our control variables (as defined in Table 1). Table 5 shows that the profile and expert rating have a positive and highly significant impact on funding success, both when run separately (Panels A and B) and jointly in a regression (Panel C). The only two exceptions relate to the expert rating which is no longer significantly associated with the probability of reaching the softcap target amount and the probability of having the tokens listed on CoinMarketCap in Panel C of Table 5. The effects are both statistically and economically important: for example, in the second column of Table 5, we find that a one-point increase in the profile or the expert rating will increase the funding percentage by more than ten percentage points. Table 5 does not show the coefficients of the control variables to conserve space.

In line with our hypotheses 1A and 2A, our results show that both profile and expert ratings are statistically and economically important determinants of funding success. These ratings serve as aggregated measures of the profile and quality of ICOs and each is an important determinant in its own right.

Table 4. ICO funding success per rating score.

Panel A: Profile rating	≤1	>1, ≤2	>2, ≤3	>3, ≤4	>4, ≤5	Above median	Below median	Test for difference
Funding success:								
Softcap hit (dummy)	0 (3)	0.231 (26)	0.278 (54)	0.508 (63)	0.821 (39)	0.627 (102)	0.253 (83)	5.45***
Funding percentage (%)	24.772 (9)	22.765(97)	25.370(184)	37.226(176)	55.406 (109)	44.179 (285)	24.480 (290)	6.25***
Funding raised (millions $)	0.932 (12)	3.341 (111)	9.022 (204)	10.252 (186)	16.144 (117)	12.527 (303)	6.796 (327)	3.05***
Token tradability (dummy)	0.5 (12)	0.297 (111)	0.382 (204)	0.565 (186)	0.812 (117)	0.660 (303)	0.358 (311)	7.94***
Panel B: Expert rating	= 1	>1, ≤2	>2, ≤3	>3, ≤4	>4, ≤5	Above median	Below median	Test for difference
Funding success:								
Softcap hit (dummy)	0 (1)	0.143 (7)	0.438 (32)	0.714 (35)	0.591 (22)	0.688 (48)	0.408 (49)	2.85***
Funding percentage (%)	28.125 (3)	13.805 (24)	22.593 (74)	39.495 (120)	65.529 (69)	54.727 (141)	24.375 (149)	7.00***
Funding raised (millions $)	1.125 (4)	4.274 (26)	9.400 (79)	11.457 (123)	20.914 (79)	17.151 (153)	8.200 (158)	2.94***
Token tradability (dummy)	0.250 (4)	0.231 (26)	0.443 (79)	0.618 (123)	0.797 (79)	0.745 (153)	0.424 (158)	6.05***

Note: See Table 1 for variable definitions. Table reports averages. Number of observations is in parentheses. The last column shows a *t*-statistic for the test for difference in means. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level.

Table 5. Determinants of funding success: Profile and expert ratings.

Variable	Softcap hit	Funding percentage	Ln(1+ Funding raised)	Token tradability
Panel A				
Profile rating (from 0–5)	0.407	0.153	2.758	0.298
	(6.54)***	(11.50)***	(14.98)***	(9.57)***
Control variables	Yes	Yes	Yes	Yes
Observations	185	575	630	630
F-Value		35.72***	33.58***	
Wald Chi^2	56.44***			131.73***
(pseudo or adjusted) R-Squared	0.373	0.313	0.337	0.328
Average VIF	1.43	1.66	1.30	1.30
Maximum VIF	2.19	3.23	1.77	1.77
Panel B				
Expert rating (from 1–5)	0.206	0.136	2.487	0.153
	(2.25)**	(5.88)***	(6.80)***	(4.01)***
Control variables	Yes	Yes	Yes	Yes
Observations	97	290	311	311
F-Value		17.99***	11.93***	
Wald Chi^2	26.40***			47.34***
(pseudo or adjusted) R-Squared	0.257	0.309	0.247	0.220
Average VIF	1.90	1.73	1.38	1.38
Maximum VIF	2.93	3.04	1.78	1.78
Panel C				
Profile rating (from 0–5)	0.783	0.146	2.757	0.268
	(4.85)***	(7.58)***	(9.60)***	(5.93)***
Expert rating (from 1–5)	−0.193	0.083	1.327	0.050
	(−1.16)	(3.51)***	(4.33)***	(1.17)
Control variables	Yes	Yes	Yes	Yes
Observations	97	290	311	311
F-Value		29.79***	19.82***	
Wald Chi^2	34.07***			73.28***
(pseudo or adjusted) R-Squared	0.564	0.416	0.453	0.342
Average VIF	1.98	1.72	1.40	1.40
Maximum VIF	2.93	3.06	1.78	1.78

Note: See Table 1 for variable definitions. The first and fourth column report average marginal effects from logistic regressions with *z*-statistics using robust standard errors in parentheses. The second and third column report OLS regression coefficients with *t*-statistics using robust standard errors in parentheses. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level. All regressions include a constant and the following control variables: Accepted currencies, Fiat currency, Ethereum platform, Ln(1+ Token price), Ln(1+ Total tokens), Ethereum return, Ethereum volatility, Ln(ICO volume). Uncapped ICO is included as a control in regressions using the Softcap hit, Ln(1+ Funding raised) and Token tradability as dependent variables. Ln(Softcap) is used as control variable in the regression using Softcap hit as the dependent variable and Ln(Hardcap) is used as a control variable in the regression using Funding percentage as the dependent variable.

Next, we investigate several determinants that, based on theory, we expect to impact funding (see Section 3). It is important to note that in our multivariate analyses we do not include the ratings. The reason is that some of the success determinants we look at are also components of the ratings (also see our variable description in Table 1). For example, the availability of a pre-ICO GitHub repository, albeit small (weight equals 6 percent), is also part of the profile rating. The first column of Table 6 shows that having a presale, and a higher number of team members positively impact the probability of hitting the softcap target amount. Funding as a percentage of the hardcap target amount, the amount of funding and the probability of getting the token traded on an online exchange tracked by CoinMarketCap are all positively impacted by having one or more GitHub repositories before the ICO, having a presale, and having more members on the project team. These findings are in line with our hypotheses 3A, 5, and 8A. Not having a bonus scheme in the public phase of the ICO and having a shorter planned duration of the campaign are positively related to funding

Table 6. Determinants of ICO funding success.

Variable	Softcap hit	Funding percentage	Ln(1+ Funding raised)	Token tradability
Independent variables				
GitHub_preICO (dummy)	0.088 (0.85)	0.081 (2.71)***	1.644 (3.91)***	0.125 (2.54)**
Insider token retention (%)	−0.311 (−1.35)	0.059 (0.99)	0.418 (0.48)	0.159 (1.45)
Presale (dummy)	0.193 (2.18)**	0.071 (2.36)**	0.926 (2.03)**	0.143 (2.74)***
Bonus scheme (dummy)	−0.142 (−1.55)	−0.062 (−2.13)**	−0.495 (−1.10)	−0.131 (−2.64)***
Duration (# days)	−0.003 (−0.95)	−0.004 (−5.47)***	−0.006 (−0.53)	−0.006 (−4.01)***
Team members (#)	0.021 (1.98)**	0.012 (6.47)***	0.221 (7.61)***	0.019 (4.16)***
Control variables				
Ln(Softcap)	−0.121 (−4.39)***			
Ln(Hardcap)		−0.085 (−5.59)***		
Uncapped ICO (dummy)	0.022 (0.07)		−0.313 (−0.38)	−0.037 (−0.39)
Accepted currencies (#)	0.012 (0.37)	−0.004 (−0.50)	0.128 (0.77)	0.005 (0.25)
Fiat currency (dummy)	0.031 (0.19)	0.107 (1.91)*	1.631 (1.88)*	−0.007 (−0.06)
Ethereum platform (dummy)	0.096 (0.64)	−0.011 (−0.26)	1.694 (2.70)***	0.134 (1.91)*
Ln(1+ Token price)	−0.027 (−0.80)	0.021 (1.45)	0.051 (0.34)	−0.027 (−1.54)
Ln(1+ Total tokens)	0.026 (0.87)	0.045 (3.00)***	0.299 (2.08)**	0.007 (0.43)
Ethereum return (%)	0.225 (1.83)*	0.071 (2.54)**	0.617 (1.92)*	−0.049 (−0.94)
Ethereum volatility (%)	1.637 (0.43)	3.561 (3.71)***	45.00 (3.73)***	5.172 (2.58)**
Ln(ICO volume) (#)	−0.251 (−1.94)*	−0.105 (−4.54)***	−1.869 (−8.05)***	−0.478 (−5.85)***
Observations	185	575	630	630
F-Value		24.11***	15.03***	
Wald Chi^2	54.40***			128.14***
(pseudo or adjusted) R-Squared	0.240	0.298	0.229	0.272
Average VIF	1.43	1.57	1.28	1.28
Maximum VIF	2.44	3.83	2.04	2.04

Note: See Table 1 for variable definitions. The first and fourth column report average marginal effects from logistic regressions with *z*-statistics using robust standard errors in parentheses. The second and third column report OLS regression coefficients with *t*-statistics using robust standard errors in parentheses. All regressions include a constant. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level.

percentage and the probability that the token is tracked by CoinMarketCap. This is consistent with hypotheses 6 and 7. However, in contrast with our hypothesis 4A, insider token retention is insignificant in all regressions. Considering the control variables, we observe that setting a higher target amount for the softcap reduces the probability of reaching that target and setting a higher target amount for the hardcap negatively impacts funds raised as a percentage of that hardcap. These findings are in line with Mollick (2014) who finds similar results in the context of reward-based crowdfunding. In some model specifications, we also find the fiat currency dummy, the Ethereum dummy, the total token supply and the market condition variables to be significant. In the next subsection, we examine the determinants of subsequent project success.

4.2. Determinants of ex-post success

This section focuses on the determinants of ex-post ICO success. We limit our ex-post analysis to 472 ICOs that were successful in raising at least 50,000 USD. The threshold of 50,000 USD corresponds with the 25th percentile of the distribution of the amount of funding raised in our sample of 630 ICOs. This removes the projects that failed to raise any money (e.g. because they were not able to reach the softcap target) from our analysis and ensures that the ex-post results are not driven by comparing projects that successfully raised money with those projects that did not.

Table 7 shows the univariate results for the profile and expert ratings split per rating score. It shows that the performance of ICOs with above-median ratings is superior compared to below-median rated token sales. We find that ICOs with an above-median profile rating have a significantly higher likelihood of their website being online in November 2019 and are more likely to have post-ICO Twitter and GitHub activity in the period between September and November 2019. The number of Tweets per week in the period from the start of the ICO until November 2019 is significantly higher for ICOs with above-median profile ratings compared to the ICOs with below-median scores. For expert ratings, we find that ICOs with above-median expert ratings show higher Twitter and GitHub activity in the post-ICO period and are less likely to end up on the graveyard.

Table 8 shows the effect of the profile and expert ratings on ex-post success measures using multivariate regressions that include the control variables (as defined in Table 1). Similar to Table 5, we do not show the coefficients of the control variables to conserve space. We find that both types of ratings are relevant and have a positive and significant impact on how well the project performs in the post-ICO period. The only exception is when using the graveyard dummy as the dependent variable (last column) in which case the coefficient of the profile rating is not significant. In addition, the profile rating loses its significance in the regressions using Tweets per week and GitHub activity as dependent variables when combined with expert ratings in the same regression (Panel C). We conclude that our results provide support for hypothesis 1B (depending on the ex-post success measure used) and strong support for hypothesis 2B.

Table 9 shows the more specific determinants that we hypothesized to impact longer-run project success. There is some support for Hypotheses 3B, 4B and 8B. Pre-ICO GitHub repositories are positively associated with the probability of having the project's website online in November 2019 and lower the probability of the token trading at a price below 10% of the issue price or the token no longer being traded

Table 7. Ex-post ICO success per rating score.

Panel A: Profile rating	≤1	>1, ≤2	>2, ≤3	>3, ≤4	>4, ≤5	Above median	Below median	Test for difference
Ex-post success								
Website online (dummy)	0.571 (7)	0.551 (49)	0.780 (132)	0.817 (169)	0.887 (115)	0.858 (239)	0.725 (233)	3.58***
Tweets per week (#)	0.538 (3)	8.053 (41)	7.686 (120)	8.597 (155)	11.231 (110)	10.588 (222)	7.108 (207)	2.99***
Twitter activity (dummy)	0.000 (3)	0.341 (41)	0.450 (120)	0.523 (155)	0.627 (110)	0.594 (222)	0.415 (207)	3.76***
GitHub activity (dummy)	0.333 (3)	0.524 (21)	0.338 (77)	0.466 (116)	0.543 (92)	0.527 (182)	0.362 (127)	2.898***
Graveyard (dummy)	1.000 (6)	0.429 (28)	0.590 (78)	0.590 (105)	0.60 (95)	0.589 (175)	0.584 (137)	0.082
Panel B: Expert rating	**= 1**	**>1, ≤2**	**>2, ≤3**	**>3, ≤4**	**>4, ≤5**	**Above median**	**Below median**	**Test for difference**
Ex-post success								
Website online (dummy)	0.000 (1)	0.583 (12)	0.800 (55)	0.788 (109)	0.909 (77)	0.824 (131)	0.805 (123)	0.39
Tweets per week (#)	0.956 (1)	4.997 (12)	6.770 (50)	10.485 (102)	11.642 (75)	10.511 (123)	8.968 (117)	0.95
Twitter activity (dummy)	0.000 (1)	0.083 (12)	0.440 (50)	0.529 (102)	0.680 (75)	0.602 (123)	0.462 (117)	2.19**
GitHub activity (dummy)	0.000 (0)	0.167 (6)	0.307 (39)	0.486 (70)	0.617 (60)	0.564 (94)	0.383 (81)	2.42**
Graveyard (dummy)	0.000 (1)	1.000 (5)	0.706 (34)	0.724 (76)	0.349 (63)	0.480 (102)	0.740 (77)	3.61***

Note: See Table 1 for variable definitions. Table reports averages. Number of observations is in parentheses. The last column shows a *t*-statistic for the test for difference in means. Only ICOs that successfully raised more than $50 k are taken into account. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level.

Table 8. Determinants of ex-post ICO success: Profile and expert ratings.

Variable	Website online	Tweets per week	Twitter activity	GitHub activity	Graveyard
Panel A					
Profile rating (from 0–5)	0.100	1.859	0.164	0.096	−0.055
	(4.91)***	(2.55)**	(5.24)***	(2.65)***	(−1.50)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	472	429	429	309	312
F-Value		4.44***			
Wald Chi^2	34.56***		52.36***	29.94***	33.88***
(pseudo or adjusted) R-Squared	0.079	0.035	0.105	0.069	0.088
Average VIF	1.35	1.34	1.34	1.31	1.35
Maximum VIF	1.81	1.80	1.80	1.71	1.75
Panel B					
Expert rating (from 1–5)	0.061	1.911	0.131	0.187	−0.180
	(1.91)*	(2.05)**	(2.99)***	(3.25)***	(−2.87)***
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	254	240	240	175	179
F-Value		1.96**			
Wald Chi^2	19.04**		29.10***	22.01***	24.31***
(pseudo or adjusted) R-Squared	0.068	0.038	0.101	0.112	0.155
Average VIF	1.45	1.44	1.44	1.42	1.43
Maximum VIF	1.99	1.92	1.92	1.94	1.95
Panel C					
Profile rating (from 0–5)	0.105	1.386	0.176	0.086	−0.062
	(4.19)***	(1.39)	(3.78)***	(1.50)	(−1.12)
Expert rating (from 1–5)	0.035	1.679	0.108	0.180	−0.177
	(1.25)	(1.80)*	(2.47)**	(3.04)***	(−2.84)***
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	254	240	240	175	179
F-Value		2.09**			
Wald Chi^2	30.95***		45.40***	27.19***	27.03***
(pseudo or adjusted) R-Squared	0.136	0.043	0.148	0.123	0.161
Average VIF	1.44	1.43	1.43	1.42	1.45
Maximum VIF	1.99	1.92	1.92	1.94	1.96

Note: See Table 1 for variable definitions. The first, third, fourth and fifth column report average marginal effects from logistic regressions with *z*-statistics using robust standard errors in parentheses. The second column reports OLS regression coefficients with *t*-statistics using robust standard errors in parentheses. Only ICOs that successfully raised more than \$50 k are taken into account. All regressions include a constant and the following control variables: Uncapped ICO, Accepted currencies, Fiat currency, Ethereum platform, Ln(1+ Token price), Ln(1+ Total tokens), Ethereum return, Ethereum volatility, Ln(ICO volume). * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level.

on an exchange tracked by CoinMarketCap. Token retention by the project team is positively related to the number of Tweets per week in the period from the ICO start until November 2019. The number of members of the project team positively relates to the probability of having an online website in November 2019, the number of Tweets per week in the post-ICO period and the probability of recent Twitter activity in the period September-November 2019.

Although we did not develop specific hypotheses concerning the ex-post performance for the other dependent variables, we do find that ICO campaigns that have been open for funding for a shorter period generate more Tweets in the period from the start of the ICO until November 2019 and are more likely to still be active on Twitter and GitHub in the period of September until November 2019. ICOs with a bonus scheme in the public phase of the selling process are associated with a lower probability of having an accessible website still. Several of the control variables (price, total token supply, and ICO volume) are significant in some model specifications.

Table 9. Determinants of ex-post ICO success.

Variable	Website online	Tweets per week	Twitter activity	GitHub activity	Graveyard
Independent variables					
GitHub_preICO (dummy)	0.137	−0.481	0.074	−0.008	−0.120
	(3.89)***	(−0.38)	(1.38)	(−0.12)	(−1.91)*
Insider token retention (%)	0.001	7.444	0.131	0.179	−0.056
	(0.02)	(2.34)**	(1.08)	(1.23)	(−0.41)
Presale (dummy)	0.017	1.949	−0.037	−0.041	−0.020
	(0.43)	(1.31)	(0.64)	(−0.60)	(−0.29)
Bonus scheme (dummy)	−0.089	−1.749	−0.091	−0.072	0.066
	(−2.17)**	(−1.46)	(−1.59)	(−1.04)	(0.94)
Duration (# days)	−0.001	−0.046	−0.003	−0.006	0.002
	(−0.52)	(−1.73)*	(−1.96)**	(−2.66)***	(1.08)
Team members (#)	0.007	0.169	0.014	0.005	−0.004
	(2.37)**	(1.70)*	(3.72)***	(1.25)	(−1.03)
Control variables					
Uncapped ICO (dummy)	0.012	0.168	0.046	0.030	−0.101
	(0.20)	(0.10)	(0.51)	(0.26)	(−0.93)
Accepted currencies (#)	0.002	0.568	0.035	−0.030	−0.013
	(0.16)	(1.21)	(1.77)*	(−1.09)	(−0.50)
Fiat currency (dummy)	−0.027	3.206	−0.131	0.055	0.090
	(−0.33)	(1.11)	(−1.28)	(0.36)	(0.62)
Ethereum platform (dummy)	−0.011	2.340	−0.011	−0.051	−0.038
	(−0.19)	(1.53)	(−0.14)	(−0.48)	(−0.41)
Ln(1+ Token price)	0.017	−0.006	−0.002	0.027	0.055
	(1.16)	(−0.01)	(−0.13)	(1.25)	(2.30)**
Ln(1+ Total tokens)	0.026	0.317	0.016	0.051	−0.023
	(1.82)*	(1.00)	(0.93)	(2.65)***	(−1.11)
Ethereum return (%)	−0.041	−0.164	−0.017	0.006	−0.022
	(−1.17)	(−0.17)	(−0.32)	(0.11)	(−0.40)
Ethereum volatility (%)	0.838	43.709	2.706	0.614	1.183
	(0.74)	(1.19)	(1.59)	(0.31)	(0.59)
Ln(ICO volume) (#)	−0.046	−1.738	−0.128	−0.046	0.128
	(−1.84)*	(−1.93)*	(−3.27)***	(−1.07)	(3.49)***
Observations	472	429	429	309	312
F-Value		3.04***			
Wald Chi^2	40.89***		48.91***	34.09***	39.67***
(pseudo or adjusted) R-Squared	0.089	0.052	0.100	0.086	0.103
Average VIF	1.33	1.33	1.33	1.32	1.33
Maximum VIF	2.14	2.14	2.14	2.02	2.10

Note: See Table 1 for variable definitions. The first, third, fourth and fifth column report average marginal effects from logistic regressions with *z*-statistics using robust standard errors in parentheses. The second column reports OLS regression coefficients with *t*-statistics using robust standard errors in parentheses. Only ICOs that successfully raised more than $50 k are taken into account. All regressions include a constant. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level.

We have conducted several additional analyses (unreported). We included dummies for the countries and categories listed in Table 2 in all our regressions. Our results are robust to the inclusion of these dummies. In all regressions, we replaced the three control variables capturing market conditions (Ethereum return, Ethereum volatility, and ICO volume) with a set of calendar month dummies. Our results are robust when time dummies are included. We also tested the robustness of the cut-off point to identify ICOs that have been successful in raising funds, for example, increasing the lower bound of funding success from 50,000 USD to 2 million USD. We rerun the regressions using the five ex-post success measures as dependent variables for the sample of 282 ICOs that raised more than 2 USD million (the median funding raised in our overall sample). Again, our results are not materially affected by the adjustment of the specification.

5. Conclusions

Initial Coin Offerings (ICOs) have become an increasingly popular way for entrepreneurs to raise money for early-stage blockchain projects until 2017, with stabilising demand in the first half of 2018 and a collapse in the second half of 2018. ICOs are fraught with asymmetric information problems between the project team and potential investors that are considering buying the tokens. This paper is the first to test whether ratings from rating websites such as ICObench can help to bridge this information gap. We find that projects that disclose more extensive information to investors (i.e. have a higher profile rating) are more successful in fundraising, and experience more post-ICO project success. In addition, a higher rating by cryptocurrency experts on the quality of the project and project team is associated with more success in fundraising and better ex-post performance. These results contribute to the existing ICO literature and underline the importance of profile and expert ratings using a rich set of funding and ex-post success measures.

Our results further show that having one or more pre-ICO GitHub repository, a presale, not making use of bonus schemes in the public phase of the ICO, a shorter planned duration of the ICO campaign, and a larger project team are positively related to funding success. Depending on model specification, we also find that having at least one GitHub repository before the start of the ICO, a shorter planned period during which tokens are sold, and a larger number of project team members positively impact ex-post project performance. These results are in line with the results of other (working) papers on ICOs (e.g. Fisch (2019), Amsden and Schweizer (2019), Lyandres, Palazzo, and Rabetti (2019), and Adhami, Giudici, and Martinazzi (2018)).

We conclude that for entrepreneurs it is important to make the ICO as transparent as possible and that for investors, expert ratings are a useful way in which to overcome the information asymmetry problems associated with token sales. Project teams that provide more and useful information to investors are more likely to successfully raise money from investors and show superior performance afterwards.

Our research demonstrates that in the ICO setting economic theory provides meaningful determinants of success, including disclosure and ratings that can reduce the information gap. We also demonstrate that many elements that are specific to ICOs have strong effects on the success in raising funding and sustaining the business. Although our study presents tests of hypotheses and detailed information on the ICOs, future research will be needed to build theory specifically for ICOs, as well as to assess the longer-term viability of ICO-funded projects.

Notes

1. CoinMarketCap checks projects that apply for admission on its platform rigorously before listing them. In order for a cryptocurrency to be considered for listing on CoinMarketCap it must have a functional website and block explorer, and be listed on a publicly available exchange with trading volume. Beyond these criteria, CoinMarketCap closely monitors both qualitative and quantitative factors. See: https://support.coinmarketcap.com/hc/en-us/articles/360034124351-Listings-Criteria.
2. Databases accessed: www.tokendata.io, www.icotracker.net, www.cryptocompare.com/ico, www.smithandcrown.com/icos, https://elementus.io/token-sales-history, www.icomarket

data.com, www.icodata.io, www.coindesk.com/ico-tracker/, www.icobench.com/ico, www.coinschedule.com, www.ico-list.com, www.icostats.com.
3. See https://medium.com/@ICObench/icobench-experts-the-importance-of-being-just-bbe07e00f73e.
4. See: https://icobench.com/stats.
5. Databases accessed: See footnote 2 for a list of databases.
6. Using the following websites: www.etherscan.io, https://wavesexplorer.com, https://blockexplorer.com/.
7. Reasons for delisting from CoinMarketCap include: low liquidity or suspicious trading activity, the project's cessation of development and/or business activity, the project's listing on CoinMarketCap was the result of misleading, incomplete, or false information, the project (and/or its associates) is under investigation, on regulator watchlists, or is found guilty of a breach of law(s), statute(s), and regulation(s), extraordinarily poor implementation or reception by the project's community or any other factor that CoinMarketCap deems risky for its users (source: https://support.coinmarketcap.com/hc/en-us/articles/360034124351-Listings-Criteria).

Disclosure statement

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References

Adhami, S., G. Giudici, and S. Martinazzi. 2018. "Why Do Businesses Go Crypto? An Empirical Analysis of Initial Coin Offerings." *Journal of Economics and Business* 100: 64–75. doi:10.1016/j.jeconbus.2018.04.001.

Ahlers, G. K., D. Cumming, C. Günther, and D. Schweizer. 2015. "Signaling in Equity Crowdfunding." *Entrepreneurship Theory and Practice* 39: 955–980.

Akerlof, G. A. 1970. "The Market for "Lemons": Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics* 84: 488–500. doi:10.2307/1879431.

Amsden, R., and D. Schweizer. 2019. "Are Blockchain Crowdsales the New 'Gold Rush'? Success Determinants of Initial Coin Offerings." SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3163849

Benedetti, H., and L. Kostovetsky. 2018. "Digital Tulips? Returns to Investors in Initial Coin Offerings." SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3182169

Buterin, V. 2017. "Analyzing Token Sale Models." Accessed 16 February 2018. http://vitalik.ca/general/2017/06/09/sales.html

Catalini, C., and J. S. Gans. 2018. "Initial Coin Offerings and the Value of Crypto Tokens." SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3143343

Chod, J., and E. Lyandres. 2018. "A Theory of ICOs: Diversification, Agency and Information Asymmetry." SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3159528

Chohan, U. W. 2020. "Initial Coin Offerings (Icos): Risks, Regulation, and Accountability." In *Cryptofinance and Mechanisms of Exchange. Contributions to Management Science*, edited by S. Goutte, K. Guesmi, and S. Saadi, 165–177. Cham: Springer.

Cointelegraph. 2017. "Fastest-Ever ICO: Ethereum-based Gnosis Creates $300 Million in Minutes, Raising $12 Million." Accessed 13 February 2018. https://cointelegraph.com/news/fastest-ever-ico-ethereum-based-gnosis-creates-300-mln-in-minutes-raising-12-mln

EY. 2017. "EY Research: Initial Coin Offerings (ICOs)." Report.

Fisch, C. 2019. "Initial Coin Offerings (Icos) to Finance New Ventures." *Journal of Business Venturing* 34 (1): 1–22. doi:10.1016/j.jbusvent.2018.09.007.

Harrison, R. T., and C. M. Mason. 2019. "Venture Capital 20 Years On: Reflections of the Evolution of a Field." *Venture Capital* 21 (1): 1–34. doi:10.1080/13691066.2019.1562627.

Howell, S. T., M. Niessner, and D. Yermack. 2018. "Initial Coin Offerings: Financing Growth with Cryptocurrency Token Sales." SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3201259

Huang, W., M. Meoli, and S. Vismara. 2019. "The Geography of Initial Coin Offerings." *Small Business Economics* doi:10.1007/s11187-019-00135-y.

Hughes, P. J. 1986. "Signalling by Direct Disclosure under Asymmetric Information." *Journal of Accounting and Economics* 8: 119–142. doi:10.1016/0165-4101(86)90014-5.

Kaal, W. 2018. "Initial Coin Offerings: The Top 25 Jurisdictions and Their Comparative Regulatory Responses." SSRN. https://ssrn.com/abstract=3117224

Kastelein, R. 2017. "What Initial Coin Offerings Are, and Why VC Firms Care. Harvard Business Review." Accessed 30 January 2018. https://hbr.org/2017/03/what-initial-coin-offerings-are-and-why-vc-firms-care

Li, J., and W. Mann, 2018. "Initial Coin Offerings and Platform Building." SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3088726

Lyandres, E., B. Palazzo, and D. Rabetti. 2019. "Do Tokens Behave like Securities? An Anatomy of Initial Coin Offerings." https://www.idc.ac.il/en/schools/business/annual-conference/Documents/2019-annual-conference/do-tokens-behave-like-securities-lyandres.pdf

Mollick, E. 2014. "The Dynamics of Crowdfunding: An Exploratory Study." *Journal of Business Venturing* 29: 1–16. doi:10.1016/j.jbusvent.2013.06.005.

Samieifar, S., and D. G. Baur. 2020. "Read Me if You Can! An Analysis of ICO Whitepapers." *Finance Research Letters* Available at. 101427. doi:10.1016/j.frl.2020.101427.

Schwienbacher, A. 2019. "Equity Crowdfunding: Anything to Celebrate?" *Venture Capital* 21 (1): 64–74. doi:10.1080/13691066.2018.1559010.

SEC. 2017. "Investor Bulletin: Initial Coin Offerings." Accessed 25 January 2018. https://www.sec.gov/oiea/investor-alerts-and-bulletins/ib_coinofferings

Spence, M. 1973. "Job Market Signaling." *Quarterly Journal of Economics* 87: 355–374. doi:10.2307/1882010.

Spence, M. 2002. "Signaling in Retrospect and the Informational Structure of Markets." *American Economic Review* 92: 434–459. doi:10.1257/00028280260136200.

Sunnarborg, A. 2017. "ICO Investments Pass VC Funding in Blockchain Market First." Coindesk. Accessed 18 February 2018. https://www.coindesk.com/ico-investments-pass-vc-funding-in-blockchain-market-first/

Varshneya, R. 2018. "Should You Launch an ICO to Raise Money for Your Startup?"Accessed 10 June 2018. https://www.entrepreneur.com/article/315873