Network Externalities in the Long-Term Performance of ICOs

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Abstract

This study examines the impact of technology and network externalities on exchange-listed Initial Coin Offerings (ICOs). Utilising an online database comprising of self-reported ICO characteristics, measures of post-ICO performance, along with information on business social networks, higher fundraising figures are found to contribute positively to the ICO long-term success. This positive impact is multiplied by six times when fundraising is conducted to an existing, proprietary blockchain. This is explained by the network effect. The modified information ratio measure is used to approximate the quality signalling of ICO organisations using price timeseries and benchmarking these to already functioning blockchain technology, e.g. ethereum in the long-term. The ICO sample's mean trading period on an exchange is 1.5 years and is used for long-period asset analysis. Additionally, the cointegration to the market technology benchmark is found to have a large, significant negative effect on long-term ICO organisational success as this indicates lower ICO intrinsic value.

JEL Classification: B26; D18; D47; G11

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1. Introduction

"Business has only two functions – marketing and innovation"

– Milan Kundera

Initial Coin Offerings (ICOs) confer transferable ownership rights in form of tokens (i.e. cryptocurrencies, digital assets or cryptoassets) to the owner. ICOs are a new fundraising instrument used to finance technological innovation against a digital voucher or receipt. They diffuse the ownership of claim for a digital good. The OECD (2019a) defines the ICOs as activity in "*creation of digital tokens by small companies to investors, in exchange for fiat currency or first-generation dominant cryptocurrencies*". They also propose that network effects are an important aspect of the economic value that is created by ICOs (OECD, 2019b). This study focuses to inspect this phenomenon.

Technology and Networks words, which can be viewed in figure 1, represent the third and fourth most frequent words used in the sample's ICO descriptions that were drawn from the ICObench database. Moreover. Blockchain, Platform and Decentralized are the most frequent words[1]. The introductions were often told in the present, nevertheless, in the majority of the cases, the ICOs product or service were not developed by the time of the ICO fundraising.

The largely unregulated nature of ICOs is said to have resulted in several fraudulent or poorly conceived offerings. Many ICOs are being described as 'frauds' (e.g. Dowlat, 2018; Shifflett and Jones, 2018). But also, the business failures can arise through poorly conceived business concepts and practises. The absence of the requirement for company legal filings and the provision of historic financial statements, along with third-party verification, often induce fallibility of self-reported information, which is to be provided to ICO investors. Hence, this study emphasizes on the determinants of the longer-term success of ICOs. This is more indicative of project quality as the market learns with time, compared to static measures of success in the previous literature, e.g. the amount of assets raised. The inquiry into the informational efficiency of the primary and secondary markets for ICO value determination is of scholarly and practical importance. In the extant literature, the determination of value for crypto assets have been considered to be challenging (Giudici et al 2020; Chimienti et al 2019;

[1] Further word frequency count was applied to the job titles between genders. These can be inspected in the figures 2 and 3.

Baur et al. 2015). The network effects in ICOs can be empirically measured and this is supportive that the ICO organisations create value through technical innovation.

Due to the novelty of ICOs, most of the recent studies of ICO organisations use the volume of the total assets raised as the main proxy of their success (e.g. Boreiko and Risteski, 2020; Campino et al., 2020; Fisch et al., 2019; Momtaz, 2018). Other studies use trading volumes on the exchanges to assess investor participation in ICOs as a proxy of the likelihood of longer-term success. (e.g Florysiak and Schandlbauer (2019); Howell et al., 2019; Sockin and Xiong, 2018). Using both proxies, Fisch and Momtaz (2020) borrow from Ritter's IPO research methodology (Ritter, 1991) and with this examine the price series and the trading volume six months after exchange listing.

This study's main approach emphasizes the long-term view of an ICO organisation and its success in innovation. Instead of the trading volume, this study is based on the presumption that relative return and volatility contain sufficient information on determining asset value from the price timeseries. Our sample comprises of ICO organisations that are listed on the exchanges and are tradable. We purport that our modified IR measure is a functional proxy for long-term performance, as it is based on the premise that successful ICO organisations exceed the technology benchmark set. Our study proposes a novel metric for measuring the network effects of ICO organisations. This is achieved through a price series analysis using the modified information ratio (hereafter IR) that benchmarks the technology or utility based on the relative value signalling information that the public market offers. This study is motivated by the need to find an alternative approach to the short-term method that may be based on investor sentiment rather than on fundamental based market information. Hence, we attempt a foundational approach to ICO organisational success, more closely linked to fundamentals. Moreover, we examine the cointegration between ICOs and the main cryptocurrencies to assess the market standing of ICO organisations through ICOs innovation rollout after they are listed on an exchange. These metrics may be conducive to provide for a more accurate valuation of ICO organisations.

The data is collected from the databases with a set criterion for data sourcing. The performance comparable market benchmark technology is ethereum, and it is utilized to measure organisations relative performances. Bitcoin was also assessed for this as well, but the ethereum was tested to be a closer, relative benchmark for the ICOs. One of the main assumptions in this study when assessing the ICO price series is that, in the long-run, the asset prices follow fundamentals. The empirical analysis in this study shows and measures that network effects contribute to the value of an ICO organisation. This can be revealed in their relative pricing. If the ICO organisation is not mature and the investor base would not find ways to contribute to its fundamentals as users by not be able to support the network effect, nevertheless, the investors may show price speculation by contributing to the investor feedback loop (Shiller, 2003). Whilst these ICOs may be susceptible to sentiment investing and speculation, these organisations are innovative. Noting this promising value, the recommendation of this study is to support the best practise foundation for these digital entities. This prompts the necessity for forming a policy to regulate for investor and user protection. The findings of this study are multitudinous but also point to the need for further study on network effects in ICOs. The results can also be useful for managing resources in ICOs, blockchain organisation or generally digital value-creating organisations. Also investing strategies in similar digital instruments can be formed with using modified information ratio. The study's long-term research focus bases on the institutions preference to invest on the long-term.

The remainder of this study is organised as follows. *Section 2* reviews the relevant literature and outlines the empirical predictions. *Section 3* presents the data, summary statistics and the empirical strategy. Then, *Section 4* presents the estimates for the variable effects and *Section 5* concludes.

2. Background and Research Questions

Scholarly inquiry into ICO organisations is a recent development. ICOs are issued on digital platforms for fundraising for innovative ventures. Noting that ICOs may engage a new investor base among retail investors, one can infer there is great potential for dynamism from the perspective of *disruptive innovation*, which at its core purports the importance of the product/service demand growth among customers that are less than institutional type (Christensen et al., 2015). Start-ups are better at innovation compared to incumbent established businesses due to their ability to focus on innovation that is apart from production and marketing (Holmström, 1989). Intuitively, this contributes to the applicability of the IR to measure the innovation against the existing market technology due to single product focus of a typical ICO organisation. The possible upend of technological innovation is raising capital in a dynamic and improved manner that is especially based on crowdfunding and enhancing liquidity among participants in the economy. These comprise a large investor base, with smaller investment proportionalities. This can contribute to the higher inclusion of investors that might not invest through the traditional platforms. This methodology also offers instant pricing and possible liquidity. Also, there seems to be a real market need for a new source of funding for these digital based organisations. Whilst the share of intangible assets in companies' value are estimated to be in figure around 80%, the start-up or SME organisations without tangible assets face difficulty in raising assets from the traditional lending sources (Ogier, 2016).

The literature stresses that investment in crypto assets entails several agency problems. For instance, Blaseg (2018) points out that the ICO market entails high information asymmetry, due its reliance on voluntary disclosures that is enforced by the unaudited investor communication and varied project quality. In the previous literature, asymmetry of information is observed when agents can benefit from withholding information where there is no requirement for external transparency (Dang, 2017). Chod and Lyandres (2019) relate Akerlof's theory (1970) *market for lemons* to describe the ICO marketplace for its unregulated nature of. Nevertheless, through listing at an exchange, the ICOs have improved their price discovery and their channels for distributing information on the quality of the project to the investors. This, however, might disappoint investors losing their invested capital.

Conversely, ICOs higher transparency through disclosures, is positively connected with the ICO success (Howell et al., 2019), as well as the ICO listing onto an exchange. In addition, Momtaz (2020) discussed the issue with ICO CEO incentives and project loyalty which may be at odds with the motivations and incentives of the investors. Similarly, conflicts of interest for motivations between entrepreneurs and investors related to the timing and the volume of distributed tokens are reported by Chod and Lyandres (2019).

2.1 Network effects in ICOs and Technology facilitation

The value creation opportunity for the ICO organisations is attractive as the digital asset market is still in its infancy and is looking for its best technology solutions and practises. For instance, drawing from the network effect framework in information technology (e.g. Weitzel et al., 2000), one can infer that, while bitcoin may be the most dominant of cryptocurrencies and digital assets, it is not dominating. By the end of 2019, no single cryptocurrency was holding a position of dominance at a near 90% level of market capitalisation. This high percentage is intuitive and lends itself from USD dollar trading volumes against other currencies or Google search engine usage that both stand at comparably similar market dominance at a near 90% level at end of 2019. For these examples, the network externalities approach suggests that there is market dominance. The lower dominance levels show a heightened probability of the market tipping to favour the competitor as a large part of the market are not utilising the largest market share holder's network system. Bitcoin's market capitalisation was estimated to be at 51.61% by Coinmarketcap[2] of all crypto assets end of 2019. It is not unlikely that bitcoin may be surpassed by other technology in the future, due to its pre-coded scalability limitations that make transactions on its blockchain more expensive when it appreciates in value, and the high latency of cleared transactions.

According to Peterson (2019) the virus-like exponential growth in bitcoin's price can be explained by Metcalfe's law (Gilder, 1993). This law is a heuristic notion that proposes that the value of a network is measured as proportional to the squared number of users, or N^2 (e.g. Hendler and Golbeck, 2007). The higher participation figures in bitcoin are not sustained in the long-term, as new owners have been motivated to trade it rather than utilise the blockchain further for real transactions in the formal economy. Metcalfe's Law calls for naïvely applying the network's valuation by treating the users equal in their participation. Whilst the growth in the network's value might not be linear, the N^2 equation of bitcoin's user number growth might not be the best descriptive model for price development (Briscoe et al., 2006). However, this rule points to the growth in value when users are added and bring along their added network externalities (e.g. Hendler and Golbeck, 2007). The value estimations would need better modelling. Dolfsma and Ende (2004) proposed the price-performance ratio as a measure to assess network effects in computing and information technology. Also, Belleflamme and Peitz (2016) propose that the peer-to-peer systems' relative quality of the users' interaction, e.g. they may contain higher quality information or assurance, also adds value to the network. Here the approach is relatively similar to capturing relative price-performance to understand the relative quality.

The challenge of ICO valuation is that whilst the ICO token may be traded on an exchange, the product/service itself may not be fully developed. Consequently, then the ICOs long-term value then would be reliant on perceived future demand-pull whilst preceding the technology-push. In addition, there are regulatory or economic structure issues that may hinder the demand

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[2] Link: www.coinmarketcap.com

even for the newly created and existing innovation. The ICOs are usually not registered legal entities such and this unregulated nature brings uncertainty in upholding economic agreements among parties and that the regions have established financial services. Heterogeneous situations would be typically expected from this environment in which emergent technology-push and demand-pull factors interact (Hyundo, 2018). In addition, as in traditional financial markets, the ICO marketplace is characterised by the presence of heterogeneous investors (Fahlenbrach and Frattaroli, 2019) but also heterogeneous users (Katz and Shapiro, 1994; Bakos and Halaburda, 2019). Some investors have shorter investment horizons and present-biased preferences and the users' preferences can hinder good's wider adaptation by limiting the network size or sustaining the existence of multiple simultaneous networks. In the latter case, if the market is undecided, and the dominating network system is more susceptible for tipping points.

Network effects are driven by the technology's ability to scale up its user base. Rather than consumer consuming a service, e.g. human-provided unit of single-use customer service, the digitally created service may be scalable among users and the duplication can be unhindered. This would suggest that these digitalised services are cheap to produce on the long term on low margins. Consequently, ICO tokens have a user and investor agency balancing dynamics, as the scalability with the cost of utility interaction seeks equilibrium for pareto optimal price. This relates to the exclusion principle on unique ownership and cost of duplication or usage. In other words, as the real returns of these digital services can be low, like in facilitating transactions, they must be high volume to attract investors. This is when the value added by user network externalities come into play. Whilst there might be a low entry point to provide these technology solutions, the network sizes and relayed externalities will matter. Therefore, whilst the technology enables, it is the demand, and specifically, in this case, the demand-side economies of scale feature that adds the value for ICOs. Bitcoin might be different from this, as to function in scale, it will require complementary services. For example, as a service that offers a payment transfer pool where the payments remain within the bitcoin pool and do not transfer on the blockchain.

Katz and Shapiro (1986) investigated the necessity of compatibility of utilities for the most superior technology. Bitcoin has relatively few extant complementaries offered compared to the USD dollar that is utilised for transacting and benchmarking many global financial instruments from e.g. mortgage rates to commodity futures pricing. The network effects of competition between complementary offerings, where participants make differentiation, was investigated by Economides and Salop (1992). They suggest that integration and compatibility are driving factors in markets as they provide more utility to users, as explained earlier with the usage of US dollars. Whilst bitcoin may serve more as a store of value, even if it was primarily designed to facilitate transactions (Nakamoto, 2008), the ethereum platform offers participants the facility for further complementary goods. In the majority of the cases, the ethereum was utilised as a platform to raise funds for the ICOs. This does not say that the ICO projects themselves would be bound to use that platform or that their offering was ready for deployment when it was created on that platform (Fahlenbrach and Frattaroli, 2019), but the tokens were offered through ethereum. These ICO tokens may have been on sale for ether, but also other currencies or fiat currencies may have been accepted.

In the literature of Initial Public Offerings (hereafter IPOs), apart from IPO characteristics, trading volume is said to be positively related to the investor sentiment as well as, their first day returns. (Baker and Wurgler, 2007). Dorn (2009) finds evidence on Internet companies' IPOs performing comparably worse in secondary markets. He purports that retail investors, guided by sentiment, push the prices above the fundamental value. Another significant factor for IPO performance is the role of the underwriter quality. Barber and Odean (2008) and Eckbo and Norli (2005) document that higher rankings of underwriters have a positive effect on IPO returns in secondary markets. There is no exact counterparty that resembles an IPO underwriter in the ICO market. The closest notion to a traditional underwriter may be the cryptocurrency exchanges that offer Initial Exchange Offers (IEOs).

ICOs, that are classified as start-ups or SMEs, are exceedingly more premature compared to traditional organisations in the IPO stage which usually have established cash flows which are then accounted for when valuing an IPO. This is the result of the greater regulation of IPO's and their related incorporations and traditional discounted cashflow valuation. Further, the traditional investment base of an IPO involves stages of earlier investment rounds from friends and family; angel investors; venture capital; private equity. After this, the market will work as the mechanism for the stock valuation. Li and Mann (2018) propose that when the 'good' is available for use, the 'wisdom of the crowd' will assess its quality and signal its economic value. These dynamics differ for ICOs. Whilst the marketing team members at ICOs contribute to the asset raising in a form of sponsoring the participation in the ICO token investing, the early stages or non-existence of the marketable good itself may be a less than optimal use of ICO organisational resources. For simplicity, the organisational manager is presumed to be restricted in allocating resources between the fund-raising/marketing and then the proposal delivery. The approach to enhance the network effects of the product by reaching out to expand the investor base is sound, but this investor base may seek to take trading profits instead of buy-and-hold. When comparing back in time the recent ICO launches to the dot-com IPO frenzy, Demers and Lewellen (2001) make the point that IPO marketing can translate for the increasing user numbers for internet companies. As follows, the pre-product ICO fundraising may thus be an underutilised opportunity and present to be less than optimal organisational growth strategy.

5.2.2 Research Hypotheses

The hypothesis can be formed that assets raised on an own ICO organisation's own propriety blockchain, instead of platforms, such as ethereum, has a positive impact on the long-term performance of that ICO organisation. The ICOs helps to gain not only investors but also users ICOs, which in effect can be presumed to described by as network effects. This can be formulated be tested empirically with using the IR measure as follows:

Hypothesis 1 (Null): Asset raising on ICOs' own proprietary blockchain does not have a positive impact on the long-run success of the organisation.

Hypothesis 1 (Counterfactual): Asset raising on ICOs' own proprietary blockchain has a positive impact on the long-run success of the organisation.

To help to make predictions for the long-term success of ICO organisations utilising the price timeseries, a presumption can be made that they can benchmarked to the extant technological innovation in the marketplace. Cointegration analysis of ICO price performance to ether can be employed to aid in that process. The cointegration will estimate the assets long-term equilibrium relationships to each other's using only the price timeseries. Moreover, Momtaz (2020b) proposes the ethereum network closeness can convey systemic risk for ICO tokens and thus introduce centralisation. The ICO organisation's own innovation can be seen as their idiosyncratic characteristics, and these show through as different price movement to the market beta or benchmark. The economic equilibrium theories support the cointegration of asset prices to the same fundamentals in the long-term (Hamilton, 1994; Johansen, 1998). While cointegration analysis has been previously employed to the ICO market index with the major cryptocurrencies (Masiak, 2019), this has not been inspected on the level of a single ICO organisation. Here cointegration relationship to the employed technology fundamental is estimated and the following hypothesis is proposed:

Hypothesis 2 (Null): Cointegration to ethereum does not have a negative relationship with market adjusted long-run returns of an ICO organisation.

Hypothesis 2 (Counterfactual): Cointegration to ethereum has a negative relationship with market adjusted long-run returns of an ICO organisation.

The ICO organisations use the internet to market their offerings through various platforms and this effect is presumed to be noticeable for the asset raise. However, inspecting the ICO teams' LinkedIn networks can help to estimate the possible marketing contribution opportunity cost from development to the ICO long-term performance. Here below is the associated null hypothesis and, for the benefit of clarity, the alternative hypothesis:

Hypothesis 3 (Null): The number of LinkedIn connections by the ICO team members does not have negative relationship with the market adjusted long-run returns.

Hypothesis 3 (Counterfactual): The number of LinkedIn connections by the ICO team members have negative relationship with the market adjusted long-run returns.

Similarly, with the team's LinkedIn connectivity, there is also the issue with later abandoned LinkedIn profiles that had been available during the asset raise. These can also be inspected for the asset raise and auxiliary inspected how these contribute to the ICO's long term performance. The below hypothesis is thus formulised:

Hypothesis 4 (Null): The number of abandoned LinkedIn profiles by the ICO team members does not have a positive relationship with the market adjusted long-run returns.

Hypothesis 4 (Counterfactual): The number of abandoned LinkedIn profiles by the ICO team members has a positive relationship with the market adjusted long-run returns.

3. Data and Methodology

To analyse ICO organisations' network effects, 3 datasets are utilised: ICO descriptive data, ICO organisation price timeseries and ICO organisation LinkedIn profile data. The multivariate regressions models including fixed country effects utilise the clustering by time for possible samples' variable heteroskedasticity. Multiple model variations are used for showing the consistency in coefficient results. This is to mitigate biases emitting from missing variables.

3.1 ICO data and summary statistics

The ICO descriptive sample consists of 675 ICOs which are drawn from the ICObench online database[3] at the end of 2019. These data are shown in Table 1. The data is self-reported by the ICO organisations through a form submission and the ICOs information entry is supervised by the database maintenance[4]. This sample only includes ICO's that have registered onto the ICObench and whose daily time-series can be sourced through Kaiko Digital Assets[5], which is a crypto asset data provider. Fisch and Momtaz (2020), utilise ICObench online information on the ICO organisations, and use Big Data technologies. The data from the ICObench for the analysis is challenging due to missing reported data. This was noted during the data pre-analysis that also included the regressions model specifications which lost power or showed lower informativeness by utilising only constructed dummy variables. This study's data capture included an additional year after Fisch and Momtaz (2020).

3 Link: www.ICOBench.com

4 The ICO registration application on ICObench is broadly the following: "Team must consist of at least 3 members with real names. White paper must be not less than 12 pages. The application must have active social links. Website must be active and do not cause suspicion."

5 Link: www.kaiko.com

Table 1

ICO descriptive summary. This table summarises the data from ICObench, self-reported ICO descriptive data, Kaiko Digital Assets price timeseries and also team member and advisor data from LinkedIn as reported on the ICObench. The data is as of 31.12.2019. The IR is calculated as the excess return of the ICO over ethereum with the excess volatility over Ethereum. The IR is winsorized between-1 and 1. The sample's employee team size is truncated to 30 whilst the advisors number by an ICO is truncated to 10.

	N	Mean	Standard Deviation	Median	Minimum	Maximum
Total Sample of ICO	675	–	–	–	–	–
Dummy - Separate Blockchain dummy	675	3.70%	0.19	–	–	–
Dummy - Ethereum cointegration dummy	675	14.37%	0.36	–	–	–
Raised 1m USD	469	29,070,646	201,321,460	10,220,400	19,121	4,197,956,135
Distributed in ICO	403	50%	21%	50%	2%	100%
Number of tokens for sale	433	35,448,395,217	670,623,877,318	201,000,000	210,000	13,950,760,545,239
Number of currencies accepted	537	1.81	1.3	1	1	9
Last day of ICO	556	24/01/2018	199.7	29/12/2017	21/08/2015	04/12/2019
Quarter	556	10.75	2.2	11	1	18
Trading days	675	536	270	568	11	1799
Token price in USD	580	204	2996	0.14	0.0001	60000
IR - winsorized - against Ethereum	675	-0.46	0.47	0	-1	1
IR - winsorized - against Bitcoin	675	-0.64	0.42	-1	-1	1
IR against Ethereum	675	-0.63	0.90	0	-13	2.1
IR against Bitcoin	675	-0.93	0.96	-1	-13	2.0
Number Team member total	622	10.20	6.2	9	1	30
# Team members – male	622	8.59	5.1	8	1	28
# Team members – female	415	1.61	1.9	1	0	12
# of Linkedin profiles by team	476	7.97	4.9	7	1	26
# of Linkedin contacts by team	508	13,441	23,103	6,436	12	332,074
# Advisor	403	5.63	2.8	6	0	10
# Advisor -male	405	5.35	2.7	5	0	10
# Advisor -female	128	0.39	0.7	0	0	5
# Team members + Advisors	626	13.78	7.3	13	1	40
Dummy - a female team member reported	675	61.15%	0.49	–	–	–
Dummy - an Advisor - female reported	675	18.96%	0.39	–	–	–
Dummy - an Advisor reported	675	59.85%	0.49	–	–	–

Table 2 compares the ICO asset raising platforms. Ethereum was reported to be utilised as a platform on 595 observations or 88% of the share. The separate blockchain or also as referred to the ICOs proprietary blockchain had 25 occurrences. That category will be used in structuring the hypothesis on network effects. ICOs' also used Waves on 10 occurrences and NEO in 8 cases. These data were also collected from the ICObench database. There were no occasions of missing data respective to this variable.

Table 2

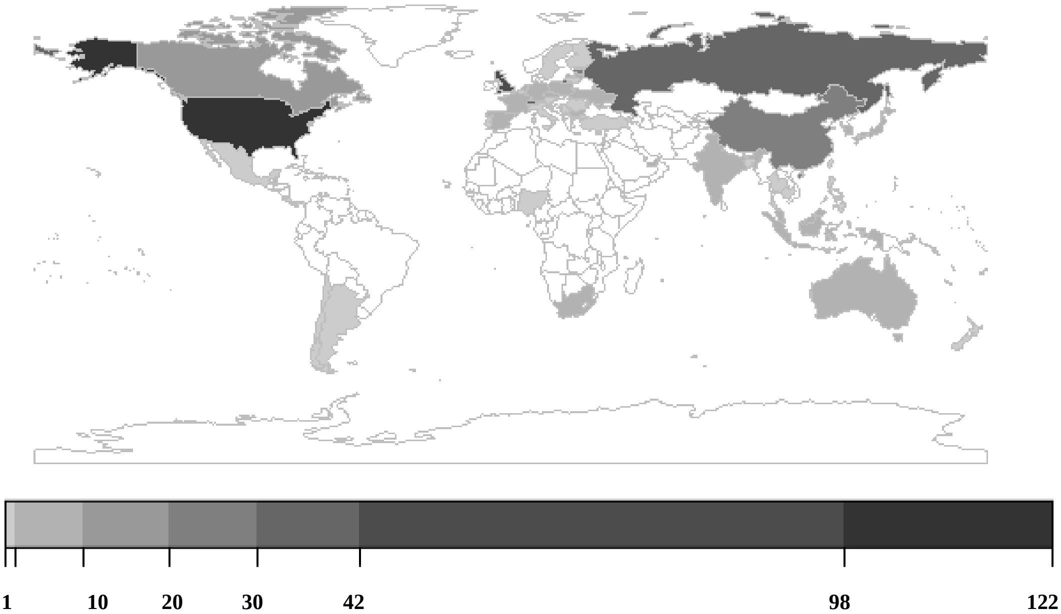
Platforms utilised for the ICOs. The ICO platform data is as reported on the ICObench database. The percentages are calculated from the sample of 675 ICOs.

	N	%		N	%		N	%
Bitcoin	4	0.6%	NEM	4	0.6%	Separate blockchain	25	3.70%
Bitcoin Gold	1	0.15%	NEO	8	1.2%	SpectroCoin	1	0.15%
BitShares	3	0.45%	NEP	1	0.15%	Stellar	3	0.45%
Counterparty	1	0.15%	Nxt	1	0.15%	Stratis	1	0.15%
EOS	2	0.30%	Omni	2	0.30%	Ubiq	1	0.15%
Ethereum	595	88.15%	QRC	2	0.30%	Waves	10	1.50%
ICON	1	0.15%	QTUM	1	0.15%	Zilliqa	1	0.15%
Infinity Blockchain	1	0.15%	Ripple	1	0.15%			
Komodo	2	0.30%	Scrypt	3	0.44%			

Table 3 provides a breakdown of ICO country domiciles. For instance, the USA was reported to be the domicile with the highest amount of ICO organisations at 122 observations. It was followed by Singapore with 98, and the UK with 44 reported ICOs. What is notable is that these countries hold both technology and financial hubs. There are country domicile regroupings to the regional level when there are less than three reported observations by country. This is to avoid interpreting intrinsic ICO project qualities as location fixed effects.

Table 3

The ICO domicile data is as reported on the ICObench database as end of 2019. The percentages are calculated from the sample of 675 ICOs. Other Africa include two Mauritius and one Nigeria ICO observations. Other America include the following ICO observations: two Argentina, two Costa Rica, two Saint Kitts and Nevis, one the Bahamas, one Chile, one Mexico and one Panama. Other Asia include the following: one Bangladesh, two Cambodia, two the Philippines, two Taiwan, one Thailand and one Turkey. Other EU include: two Austria, one Belgium, two Cyprus, two Finland, two Italy, one Luxembourg, one Portugal, one Romania and one Sweden. The Other Europe include the following ICOs: one Armenia, two Lichtenstein, one San Marino and one Serbia.



	N	%		N	%
Belize	5	0.7%	Oceania	12	1.8%
British Virgin Islands	6	0.9%	Poland	4	0.6%
Bulgaria	4	0.6%	Russia	36	5.3%
Canada	18	2.7%	Seychelles	4	0.6%
Cayman Islands	15	2.2%	Singapore	98	14.5%
China	24	3.6%	Slovenia	10	1.5%
Czech Republic	3	0.4%	South Africa	3	0.4%
Estonia	21	3.1%	South Korea	8	1.2%
France	6	0.9%	Spain	4	0.6%
Germany	9	1.3%	Switzerland	42	6.2%
Gibraltar	15	2.2%	UK	44	6.5%
Hong Kong	20	3.0%	Ukraine	3	0.4%
India	6	0.9%	United Arab Emirates	5	0.7%
Indonesia	4	0.6%	USA	122	18.1%
Israel	8	1.2%	Other Africa	6	0.9%
Japan	9	1.3%	Other America	10	1.5%
Latvia	5	0.7%	Other Asia	9	1.3%
Lithuania	7	1.0%	Other EU	13	1.9%
Malaysia	4	0.6%	Other Europe	5	0.7%
Malta	7	1.0%	NA	36	5.3%
Netherlands	8	1.2%			

3.2 ICO organisation price time-series

Kaiko Digital Asset sourced ICO organisation price timeseries from various crypto exchanges were used to calculate the Information Ratio (IR) on daily close prices at UTC midnight[6]. The analysis utilises IR due to its applicability to measure market relativeness while utilising the marketplace's price signalling on the ICO organisation quality. The IR is calculated as the excess return of the ICO token R_i over ether R_{ETH}, in proportion of compared excess volatility σ_{iETH}. To formulate the equation:

$$IR_i = \frac{E(R_i - R_{ETH})}{\sigma_{iETH}} \qquad (1)$$

The presumption is made that ICO organisations with a single business aim are seeking to create a value-added innovation over the base market platform technology, such as ethereum, and thus it may be compared to this benchmark. This is a novel approach to assessing the quality solely on the price series. Other existing approaches may mix these with ICO market capitalisation, the number of users or by trade volume. With the IR approach, the intuition is to capture the long-term fundamental value of these projects, and possible utility and mitigate the inputs from short term sentiment trading. Owning to the existence of the ICO organisations marketing efforts after the ICO and absence of securities market regiments governing investor relations, the cause of investor sentiment may not be considered exogenous as in the stock market (e.g. Baker and Wurgler, 2007). The research into the success of the ICO organisation in the long-term, and this might imply a technological innovation value in the form of network effects and cointegration. The IR may be used to assess investments by their consistency of surpassing the market and this makes it more applicable to market relative comparison than Sharpe Ratio (Sharpe, 1994). In addition, Sharpe Ratio relates to the market to risk-free rate as well as the to the differing volatility. Here it is assumed a benchmark measure to compare an ICO to already functioning technology such as ethereum.

ICO tokens are tradable 7-days a week and 24-hours a day. The timeseries is selected by its earliest exchange listing to any quoted currencies. These may be quoted in bitcoin, ether, tether, BNB, quantum, OKB, dogecoin, US dollars, CKUSD, EOS, HT, Chinese renminbi, Australian dollar or South Korean won and the series are then converted into the USD. The

[6] For the information completeness, CoinMarketCap and Coingecko were also utilised as auxiliary data source.

mean history of the sample's trading days is 534 days and were calculated until the year-end of 2019.

This analysis applies ethereum as the primary market performance benchmark, as the sample's ICO tokens daily returns show higher correlation of 0.293 and have 100 assets cointegrated with it. The test specifications are presented in appendix 2. The comparable for bitcoin are 0.26 and 86. Moreover, 88.2% (595) of the sample's 675 ICOs have utilised ethereum as their funding and possibly operational platform. Four ICO organisations utilised bitcoin for asset raise, which represented less than 0.6% of the sample.

The sample's median price is 0.14 USD. The mean of annualised volatility of the ICO sample is 362%. This is very high even when it is compared to the annualised volatilities of ether at 134% since its launch in August 2015 or bitcoin's 77% during the same period. The mean annualised return of the ICOs across the time periods is -248%, with a median annualised return of -185%. The ICOs' IRs are winsorized between a range of -1 and 1 to deal with the outliers. Moreover, heuristically in investing, IR of -1 indicates a very poor performance whereas IR of 1 shows a great performance. The winsorized IRs to ethererum have a mean of -0.47 with a standard deviation of 0.5. The equivalent figures for the bitcoin winsorized IRs are -0.62 with 0.5.

5.3.3 ICO organisation LinkedIn profile data

A secondary investigation is also made into the composition of the human capital and networks within the ICO industry. The human capital information was extracted from the ICObench database using a web crawler technology. Based on the reported team information in the ICObench database, the dataset has 8,672 ICO organisation members of both team members and external advisors. The male employees represent 81.3% of the sample (i.e. 5,346 individuals) with the figure for 18.7% female employees (i.e. 1,001 individuals). The ICObench database also lists project advisors. The sample consists of 2,325 advisors of which only 6.8% are female. The online Gender-API[7] was utilised as the gender definition tool in this study. The gender suggestion was made with the input date of name and country when this data was available.

The LinkedIn profiles were the most reported social media platform in the ICObench database. Another web crawler was utilised to search for the title, location, number of

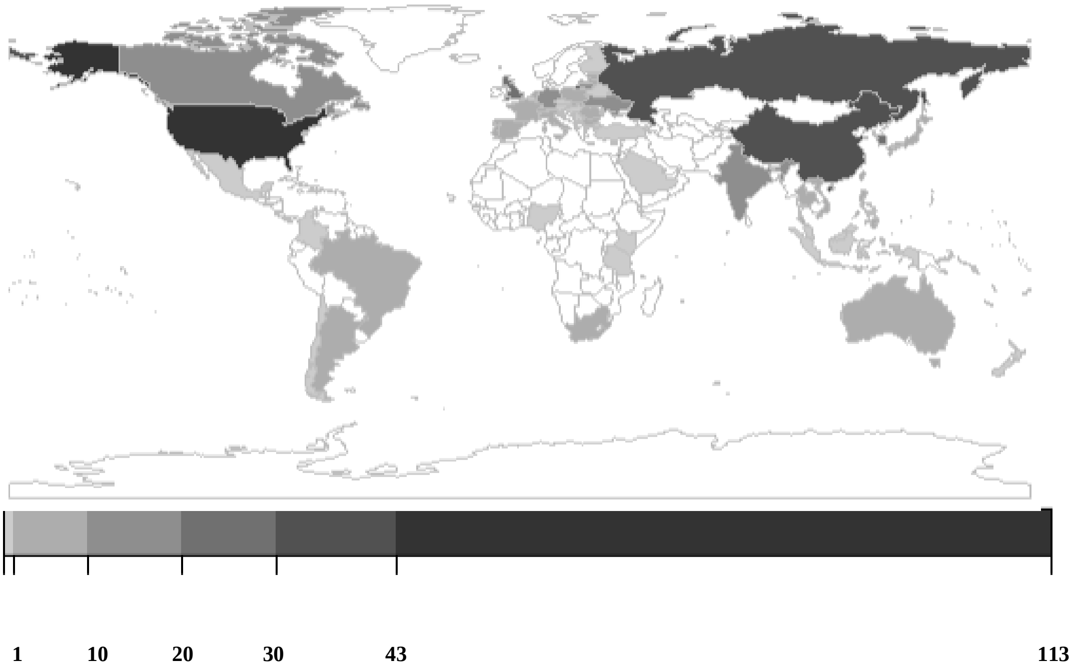
[7] www.gender-api.com

connections as well as a number of followers through the direct profile links provided on the ICObench. On average, the sample's male team members are estimated to have 1,822 connections (N: 4,328), whilst the females have 1,350 (N:692). Other social media listed were Twitter, Facebook as well as GitHub. The presumption is made that these reported LinkedIn profiles are not time-varying on ICObench due to the sample's 385 reported no-more existing LinkedIn profiles at end of 2019. LinkedIn profiles are generally assumed to help in branding personal career profiles rather than only for an opportunity/job duration. The sample's 65.9% share of the male advisors had reported a LinkedIn profile in the ICO database. They had an average of 19,559 LinkedIn contacts. The equivalent figures for female advisers are 87.4% with an average of 3,586 LinkedIn connections. Due to the data limitations[8], which is expected to affect the groups equally, the number of connections is a downward estimation. Table 4 presents the ICO organisations' reported team member's highest frequency cluster by country or region as reported on LinkedIn profiles sampled from ICObench. The USA, Russia and China were the most usual locations for ICO organisations' team member clusters. There are regional regroupings for the LinkedIn country locations when there are less than three ICO observations by country.

8 As by a default profile setting, LinkedIn may only show "500+ connections" rather than the exact figure.

Table 4

Linkedin team locations. The highest number team member location by country data is gathered from the reported LinkedIn profiles in the ICObench database. The percentages are calculated from the sample of 675 ICOs. African locations include ICOs: one Kenya, one Nigeria and one Tanzania. Oceania includes: eight Australia and one New Zealand. Other Americas include one Chile, one Columbia and two Mexican ICOs. Other EU include two Austria, one Belgium, two Cyprus, one Czech Republic, two Finland, one Hungary and two Malta. The Other Europe include an ICO from Armenia, Belarus, Liechtenstein, Monaco and Serbia.



	N	%		N	%
Africa	8	1.2%	Russia	43	6.4%
Brazil	3	0.4%	Singapore	16	2.4%
Bulgaria	7	1.0%	Slovak Republic	3	0.4%
Canada	18	2.7%	Slovenia	10	1.5%
China	33	4.9%	South Korea	24	3.6%
Estonia	5	0.7%	Spain	5	0.7%
France	7	1.0%	Switzerland	10	1.5%
Germany	11	1.6%	Taiwan	3	0.4%
Hong Kong	7	1.0%	Thailand	4	0.6%
India	13	1.9%	UK	29	4.3%
Israel	11	1.6%	Ukraine	13	1.9%
Italy	6	0.9%	USA	113	16.7%
Japan	6	0.9%	Vietnam	4	0.6%
Latvia	3	0.4%	Oceania	9	1.3%
Lithuania	15	2.2%	Other Americas	7	1.0%
Netherlands	3	0.4%	Other Asia	6	0.9%
Philippines	3	0.4%	Other EU	11	1.6%
Poland	3	0.4%	Other Europe	6	0.9%
Portugal	4	0.6%	NA	190	28.1%
Romania	3	0.4%			

ICO organisations are deemed to be highly human capital intensive (Campino, 2020). And this study draws on accessible online data to see if there can be made a differentiation between marketing and development roles or ICO resource allocation. The sample's female participation as team members and advisors is 13.4%. This is a very low figure across all the industries, especially when this figure encompasses all occupational roles including e.g. development and marketing and seniorities. To illustrate, the estimation of women working in technology-related roles stand at 15%[9]. In financial services, this figure is nearly at parity 50% across all the occupational roles, but majority in less senior level roles which has been an area of that is addressed (Catalyst, 2020). This lower comparable seniority is also seen in this study's ICO team sample when looking at the figure 2 and 3 job role title wording between the men and women. Beside the technology skill gap, this could also be an indication that ICO organisations are perceived to be riskier organisations for careers (Claussen et al., 2016) and females are perceived to be more risk averse in general (Eckel and Grossman, 2008; Borghans et al., 2009). The figures have an indication of the occupations present at ICOs: male (Figure 2). and female (Figure 3.) titles including the advisors. For men, the highest frequency titles relate to the words of 'developer', 'co-founder' and 'CEO', whereas for women, the 'manager', 'marketing' and 'head' are more prevalent. The female titles resonate less senior as well as pointing toward involving business development tasks rather than product development. When crudely comparing the developer word frequency in job titles, 5% of women team members included this whilst the equivalent was 11% for men. This represented men's highest frequency word in the job title, whilst this was the 6th for women.

The ICO organisations are by majority small-sized teams. Out of 675 of the observed ICOs, only 12 of them have more than 30 employees. This corroborates with previous findings (OECD, 2019b; Howell et al., 2019), which describe these organisations as micro-SMEs. The sample only includes 30 first reported employees and 10 first reported advisors. The sample's reported mean team size is 10 members. The equivalent mean advisor number is six by an ICO organisation.

9 PWC, Women in Tech: Time to close the gender gap, 2017.

3.4 Empirical strategy

We estimate Tobit models (Tobin, 1958) of ICO long-term success relative to the market by employing the IR measure constraining the scores between -1 and 1. The base model, in which the restricted IR of the ICOs is the dependent variable, is estimated in the following form:

$$IR_i \quad = \beta_0 \ + \beta_1 R_i + \beta_2 \ O_i + \beta_3 (R_i \times O_i) + \ \varepsilon_i \tag{2}$$

where: $IR \epsilon [0, 1]$, representing market adjusted performance to ethereum. R denotes the amount of assets raised in USD millions. O denotes the foundation upon own proprietary blockchain and ε_i is the error term. The interaction between assets raised (R) and own, proprietary blockchain (O) is used as a proxy to measure the network effects.

To establish robustness, an alternative variable to assets raised is used, which also caters to explanatory power lost by missing values.

Hence, our second specification used the number of tokens (T), the price of a token (P), own proprietary blockchain (O) and the following interaction terms:

$$\begin{aligned} IR_i \quad = \beta_0 + \beta_1 T_i + \beta_2 P_i + \beta_3 O_i + \beta_4 (T_i \ \times P_i) + \beta_5 (P_i \times O_i) \\ + \beta_6 (T_i \times O_i) + \ \beta_7 (\mathrm{T} \times P_i \times O_i) + \ \varepsilon_i \end{aligned} \tag{3}$$

In our third specification, we incorporate the cointegration between the ICO organisation and the price of ethereum, in the form of a dummy variable CI_i^{eth} which take values 0 or 1. The steps for the cointegration can be viewed in appendix 2.

$$IR_i \quad = \beta_0 \ + \beta_1 R_i + \beta_2 \ O_i + \beta_3 (R_i \times O_i) + CI_i^{eth} + \ \varepsilon_i \ , \tag{4}$$

The specifications one, three and five include the reported country domicile variables. The specifications two, four and six include the team location variables.

Table 7 describes the explanatory factors for the ICO's asset raising success that is defined as Logarithm of 1 million USD raised using the least ordinary squares model (OLS). These regressions are auxiliary in the investigation the organisations long-term success from the outset of this ICO sample. In other words, this is not a representative sample of all ICOs, but only this study's sample and which are registered onto an exchange. Hence this sample may show survivorship bias against the ICO universe. Generally, Table 7 regressions specifications can be formulated as:

$$Log(\ 1USDM_i\ ) = \beta_0 + \beta_1 D_i + \varepsilon_i \qquad (5)$$

The regressors in *D* represent variables such as dummy variables of team, advisor, LinkedIn and domicile reporting on ICObench; number of LinkedIn contacts (log), abandoned LinkedIn profiles, (log) tokens for sale and (log), price in USD, and ICO end date by quarter. The proprietary blockchain dummy variable was also regressed with the dependent variable during pre-analysis, but this did not provide any significant results. For the result robustness, there are eight specifications, including two specifications with fixed effects on country team location, as gleaned from LinkedIn, and reported domicile as shown in the ICObench database, to assess the variables effects which may again have different sub-sampling due to missing observations.

4 Results

Table 5 and 6 present the Tobit regression estimates of ICOs computed IRs against ethereum. This is winsorized between -1 and 1. This score sums up to 2 and thus it will give the coefficients estimates the percentage magnitude that is divided by 2. Columns 1, 2, 6, 7, 8 and 9 of Table 5 present specifications with a single control variable, as a starting point of the analysis. Table 6 present the results similarly to Table 5, but includes control variables specification. Table 7 shows the regression results for the asserts raised and variable relationships. These results are discussed thematically below.

4.1 ICO Technology and Network effects

The network effects can be seen in pricing of the exchange listed and trading ICO when proprietary blockchain is already functioning. The base model in columns 3 table 5 present the interaction result of the IR for whether the assets were raised on to the proprietary blockchain by the ICO. Whilst the 100m USD raised shows 1% positive and highly significant effect on the IR score, the interaction of assets raised on a proprietary blockchain showed a 6% effect at high significance. This effect is estimated to be six times larger compared to the only assets raised coefficient. Specification 5 includes an additional cointegration variable. The results persist as they are comparably similar by sign, magnitude and significance as shown in column 3. As can be seen across all the specifications in that same table, the own blockchain variable that aggregates all the existing and own blockchain but differing technologies (or purposes) does not have any significant effect.

Table 5

ICO's IR against Ethereum and variable relationships

This table reports Tobit regression estimates. The dependent variable is the IR of the ICOs to ethereum. The scores are censored between -1 and 1. The standard errors are clustered by ICO end date quarters and are shown in brackets. The asterisks denote the following levels of significance: ***<0.01, **<0.05 and *<0.10.

Panel A	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Raised-$100M-USA (R)	0.029*** [0.01]	–	0.021*** [0.005]	–	0.020*** [0.005]	–
ETH cointegration (E)	–	--0.258*** [0.058]	–	–	-0.234*** [0.167]	-0.260*** [0.058]
ETH platform	–	–	–	–	–	-0.109 [0.082]
1bn Tokens for sale (T)	–	–	–	0.002*** [0.001]	–	–
Price of ICO token USD (P)	–	–	–	0.004** [0.0001]	–	–
Own Blockchain ICO (O)	–	–	-0.009 [0.145]	-0.182 [0.196]	-0.001 [0.143]	-0.071 [0.148]
Interaction: R*O	–	–	0.127*** [0.019]	–	0.123*** [0.019]	–
Interaction: T*P	–	–	–	-0.004*** [0.001]	–	–
Interaction: P*O	–	–	–	-0.021*** [0.005]	–	–
Interaction: T*P*O	–	–	–	0.146*** [0.036]	–	–
Log Sigma	-0.592*** [0.039]	-0.539*** [0.037]	-0.600*** [0.039]	-0.563*** [0.049]	-0.612*** [0.045]	-0.539*** [0.037]
Log-likelihood	-410.91	-615.54	-408.28	-426.81	-402.85	-614.67
Wald χ^2	5.03**	15.23***	10.39**	14.34**	21.53***	16.99***
# Observations	469	675	469	402	469	675

Panel B	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
ICO end date by quarter	-0.035*** [0.011]	–	–	–	–
Team Member	–	-0.034** [0.014]	–	–	–
Team Member male	–	0.038** [0.018]	–	–	–
10k LinkedIn contacts team	–	–	-0.278** [0.117]	–	–
Abandoned LinkedIn profile	–	–	–	-0.048** [0.023]	–
Advisory dummy	–	–	–	–	-0.001 [0.086]
Log Sigma	-0.578*** [0.036]	-0.527*** [0.039]	-0.528*** [0.044]	-0.517*** [0.035]	-0.525*** [0.037]
Log-likelihood	-489.45	-576.64	-438.21	-577.09	-623.12
Wald χ^2	9.675***	5.370*	3.950**	4.457**	0.001
# Observations	556	621	476	622	675

Further, table 6 presents the 100m USD raised on that proprietary blockchain interaction in columns 1, 2, 5 and 6. These specifications include cointegration indicator and location fixed effects. The coefficients in all specifications stay highly significant with large effects between 6.3% to 12%. Estimates in columns 5 and 6 are controlled with social media variables and show the higher coefficient effects at 12% for this variable interaction. This may be explained by the lost power of losing observations due to missing values, but most importantly the interaction variable of assets raised on own blockchain remains large and significant. The specifications 1 and 5 include domicile location fixed effects, whilst the specifications of 2 and 6 include the LinkedIn profile team location fixed effects. The sign, magnitude and significance stay comparably similar.

For robustness, estimate 6 in table 5 is included to check for any variable collinearity of own blockchain, ethereum platform-based fundraising and cointegration. To mitigate any model sample selection bias and aid the result robustness due to those missing values, also a further proxy for asset raised success was introduced. This was formulated by interacting the number of tokens sold and the token price variables. The number of tokens sold and the token price proxy relationship to the log asset raised dependent variable is explored in columns 7 and 8 in table 7. This proxy is similar when interacted further with the indicator variable of the proprietary blockchain. The specifications 4 in table 5 explores this asset raise proxy's coefficient effect. The coefficient effect magnitude is similar at 6.5% whilst being moderately significant. Columns 3 and 4 in Table 6 aim to replicate the prior specifications 1 and 2. These respective specifications show positive, 6.5% and 7.5% coefficient effects for the asset raise and ICO's own proprietary interaction with both being highly significant. Thereby, the null hypothesis, H1(0), of the interaction of assets raised with own proprietary blockchain having no positive impact on ICOs long-term performance can be rejected. This impact, over merely the amount of assets raised, can be explained through available user utility or as the network effect. This assessment supports the study by Uzzi (1991) that evidenced that organisations that create network effects have better chances of survival.

Table 6

ICOs' IR against Ethereum and variable relationships including domicile and LinkedIn team location

This table presents estimates of Tobit regressions. The dependent variable is the IR to Ethereum. The IR scores are censored between -1 and 1. The results do not display the insignificant coefficients estimated to be less than 5% of significant of team locations or ICO domiciles. The complete list country/regions can be seen in tables 3 and 4. The standard errors are clustered by ICO end date quarters and are shown in brackets. The asterisks denote the following levels of significance: ***<0.01, **<0.05 and *<0.10.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Own Blockchain ICO (O)	-0.054	0.023	-0.234	-0.156	-0.068	-0.090
	[0.122]	[0.116]	[0.162]	[0.156]	[0.147]	[0.146]
Raised-$100M-USA (R)	0.020***	0.017**	–	–	-0.086**	-0.093**
	[0.004]	[0.007]			[0.040]	[0.038]
1bn Tokens for sale (T)	–	–	0.0001***	0.0001***	–	–
			[0.0000]	[0.0000]		
Price of ICO token by USD (P)	–	–	-0.00001	0.00001	–	–
			[0.00002]	[0.00002]		
ETH cointegration (E)	-0.175***	-0.180***	-0.219***	-0.205***	-0.145***	-0.173***
	[0.048]	[0.046]	[0.053]	[0.048]	[0.056]	[0.054]
<u>R*O</u>	0.141***	0.126***			0.239***	0.241***
	[0.029]	[0.018]			[0.049]	[0.043]
T*O	–	–	0.001***	0.001***	–	–
			[0.0002]	[0.0002]		
P*O	–	–	-0.018***	-0.022***	–	–
			[0.006]	[0.004]		
T*P	–	–	-0.0001***	-0.0001***	–	–
			[0.00002]	[0.00002]		
<u>T*P*O</u>	–	–	0.125***	0.157***	–	–
			[0.039]	[0.030]		
ICO end date by quarter	-0.013	-0.008	0.001	0.0005	-0.006	-0.004
	[0.010]	[0.011]	[0.013]	[0.013]	[0.014]	[0.013]
10k LinkedIn contacts by team	–	–	–	–	-0.176**	-0.137*
					[0.075]	[0.080]
Abandoned LinkedIn profile	–	–	–	–	-0.033*	-0.035*
					[0.019]	[0.020]
Number of team members	–	–	–	–	-0.008	-0.012
					[0.013]	[0.013]
Team member male	–	–	–	–	0.012	0.017
					[0.016]	[0.016]
Country: Domicile (1, 3, 5) and LinkedIn Team (2, 4, 6)	–	–	–	–	–	–
Domicile: Africa	-0.233	–	-0.331**	–	-0.154*	–
	[0.150]		[0.147]		[0.084]	
Domicile: Bulgaria	0.252	–	0.166**	–	0.098	–
	[0.211]		[0.071]		[0.143]	
Domicile: China	0.319*	–	0.504**	–	0.142	–
	[0.193]		[0.230]		[0.312]	

Table 6 continued in the following page.

Table 6 continued in the following page.

Domicile: Japan	0.041	–	-0.142	–	-0.491***	–
	[0.230]		[0.168]		[0.090]	
Domicile: Oceania	0.149	–	0.391***	–	0.348	–
	[0.200]		[0.129]		[0.249]	
Domicile: Other Americas	0.207	–	0.447**	–	0.308	–
	[0.209]		[0.203]		[0.253]	
Domicile: Poland	-0.351**	–	-0.374***	–	-0.245	–
	[0.160]		[0.134]		[0.187]	
Domicile: Seychelles	0.381***	–	0.336**	–	0.618***	–
	[0.116]		[0.148]		[0.084]	
Domicile: South Korea	-0.436***	–	-0.421***	–	-0.416***	–
	[0.085]		[0.101]		[0.117]	
Domicile: Ukraine	0.076	–	0.513***	–	0.098	–
	[0.217]		[0.071]		[0.233]	
Domicile: United Arab Emirates	-0.140		-0.329**		0.175*	
	[0.182]		[0.160]		[0.106]	
LinkedIn team: Brazil	–	-0.090	–	0.245**	–	-0.106
		[0.288]		[0.113]		[0.302]
LinkedIn team Canada		-0.172		-0.350**		-0.216
		[0.154]		[0.143]		[0.161]
LinkedIn team: France	–	-0.301**	–	-0.325**	–	-0.270*
		[0.134]		[0.130]		[0.146]
LinkedIn team Italia	–	-0.259		-0.308**		-0.273*
		[0.163]		[0.156]		[0.162]
LinkedIn team: Japan	–	-0.644***	–	-0.513***	–	-0.666***
		[0.118]		[0.178]		[0.128]
LinkedIn team Lithuania	–	-0.347**	–	-0.310**	–	-0.355**
		[0.140]		[0.157]		[0.146]
LinkedIn team Oceania	–	0.372	–	0.431***	–	0.419
		[0.339]		[0.164]		[0.308]
LinkedIn team Other America	–	0.444***	–	0.550***	–	0.370**
		[0.156]		[0.115]		[0.150]
LinkedIn team Philippines	–	0.105	–	0.339***	–	0.120
		[0.220]		[0.118]		[0.186]
LinkedIn team Thailand	–	-0.221	–	-0.472***	–	-0.250
		[0.170]		[0.118]		[0.171]
LinkedIn team Vietnam	–	-0.464***	–	0.081	–	-0.497***
		[0.122]		[0.253]		[0.127]
LinkedIn team and Domicile: UK	REF	REF	REF	REF	REF	REF
Log(scale)	-0.832***	-0.842***	-0.821***	-0.831***	-0.825***	-0.850***
	[0.038]	[0.037]	[0.042]	[0.042]	[0.044]	[0.041]
Log-likelihood	-279.804	-275.225	-245.882	-241.840	-211.608	-202.936
Wald χ^2	61.887**	72.385***	67.452**	77.028***	51.873	72.275**
# Observations	469	469	404	404	351	351

4.2 Cointegration in ICOs

Tables 5.5 and 5.6 report highly significant and strong effects for the cointegration indicator variable. For instance, specification 2 in table 5 presents a negative coefficient effect for cointegration with ethereum at -12.9% on high significance. Table 5 columns 5 and 6 show similar results -11.7% Table 6 across all specifications show comparable effects ranging between -7.5% to -10.5%. We can thus reject the null hypothesis of the cointegration not having a negative impact on long-run ICO organisation performances. The cointegration has a strongly significant negative effect. This corroborates further Fahlenbrach and Frattaroli (2019) discovery on their application of “lottery feature” for ICOs. By this they posit that investors are attracted to the idiosyncratic volatility in investments. Own, proprietary technological innovation creates value that will have a differentiating asset base to the market. Intuitively, the ICOs with this intrinsic value feature can function as diversifying assets in a portfolio. As per figure 1 in appendix 1 the ‘decentralised’-word that relates to decentralized decision making, but intuitively also relating to systemic risks, is stated in excess of 30% of the ICO organisational marketing introductions. Noticeably, bitcoin was introduced during the aftermath of 2008-2009 financial crisis that a had large systematic impact on markets. Out of the 25 own blockchain sample observations, 3 ICO organisations’ price series were cointegrated with ethereum. This cointegration variable is endogenous in nature and thus can be explained with other variables. However, this metric helps to indicate ICO’s market standing from the price series and functions well as a control variable with providing result consistency. This is important as the sample loses power when more variables are used due to missing values or the use of only indicator variables. Further future analysis is encouraged for and with this metric.

4.3. Supporting ICO long-term or asset raising success factors and indicators for the IR measure.

This section attempts to place the IR measure with previous empirical findings. In conjunction it also investigates the ICO organisations' social media presence and team's time usage contribution to the project's long-term performance. Their impact on the ICO asset raise is also assessed to see the outset for the project development. This might help to form an understanding ICO organisation's resource allocation between innovation and marketing. The third hypothesis tests the empirical validity of the ICO organisation team LinkedIn 10k connections impact on the ICO's IR measure. The estimates in specification 9 in table 5 shows a highly significant negative effect of -8.5% for 10,000 LinkedIn connections by the ICO teams. Columns 5 and 6 in table 6 show the team's LinkedIn 10k connections coefficient effects with cointegration indicator, the timing variable and country fixed effects. Specification 5 shows with the domicile fixed effect variable -8.2% effect with a moderate effect and then specification -6.5% with lower significance with the LinkedIn gleaned team location fixed effect variable. It can thus be said with a degree of confidence that the null hypothesis of the third prediction can be rejected and the alternative can be accepted.

The fourth hypothesis also explores the role of social media in the organisation's post-ICO performance. Specification 10 in table 5 shows -1.9% of the abandoned LinkedIn profile by the team to the IR performance at a moderate level of confidence. Table 5 also shows that the effect is -1.55% at a low confidence level. Table 6 shows similar coefficient effects for specification 5 at -1.6% and for specification 6 at -1.75% both at a lower level of confidence. Whilst there is an indication of this consistently sized and negative effect, the results remain weak for not all reaching over 5% significance. The prudent approach is to consider the last hypothesis test inconclusive. These test results may support the conclusion of hypothesis 3 on social media as the test results all showed 10% significance. But most notably, the team's LinkedIn network size indicates to be a stronger explanatory variable. Both variables will be assessed in conjunction with this data samples ICO organisations' asset raise later in this section.

Whilst these variables may work as proxies for ICO's social media presence, they also are an indication of team member's time deployed that is limited resource. These variables have decreasing effect for the long-term ICO performance. The results corroborate Brown et al. (2020) findings on limited time as resource through their analysis on the time spent on social media, e.g. information sourcing versus time spent on trading.

Indirectly relating back to the human capital factors as much as the word frequency analysis of team member titles comparison allows between figure 2 and 3 in appendix 1 by gender, the gender does not seem to influence assets raised. Also, the team size does not seem to have a significant effect. Both these variable coefficient effect results are in modest contrast to the results that are evidenced earlier in in specification in table 5. Where the estimations show moderate significance for a negative impact for larger team but a positive impact for an increase of a male team member. When ICO organisations function with limited resources the increase in resources to product or good design delivery, or development over marketing has a positive effect on the long-term ICO project success. For the ICOs, the hiring of business development personnel on the expense of product development in the early stages of companies may be detrimental to organisational performance. Fahlenbrach and Frattoli (2019) find that many investors sell their tokens before the product is developed. ICO organisations may underutilise the opportunity by sponsoring, or marketing, immature technology with the aim to create the desired network effects. The prices would be expected to correct downward, especially if the markets lack those ICO token users. The further inspection shows that whilst these variables keep persistent signs and effects, they lose their significance as shown in columns 5 and 6 in table 6 as the sample reduces due to missing observations. The social media derived variables keep a degree of significance in this smaller observation regression.

The timing of the end-date by quarter has a moderately significant negative relationship for long-term ICO price performance when inspecting estimates 7 in table 5. A one-year ICO ending date has a 3.8% negative effect on the IR measured performance. When the ICO launch date variable is included with other explanatory variables in all 6 columns in table 6, there are no demonstrably significant or large coefficient effects to the ICOs long- term performance.

Table 6 provides a view of the country fixed effects by domicile and by LinkedIn gleaned team location against the UK that was set as the reference country. The most consistently strong significant effects by domicile are the coefficients by Seychelles between 16.9% and 30.9% and by South Korea between -20.8% and -21.8%.

The most consistently large, significant effects by LinkedIn team location are shown by Japan at results between -25.7% and -33.3%. The other countries in America LinkedIn team indicator, which include Chile, Columbia and Mexico, display high positive effects between

22.2% to 27.8% at high to moderate significances. France, Lithuania and Vietnam show negative coefficients that also show moderate to high significances. Table 6 does not show coefficient effects for the locations without 5% or higher significance. The locational impact on asset raise effects are inspected closer in table 7.

The regression estimates were controlled both with location domicile and LinkedIn team location variables for robustness. The columns that use LinkedIn location variable show consistently higher explanatory power as indicated by the Wald-test measure. Most notably this can be seen in columns 5 and 6 in table 6. Further, according to the Wald-test results for the regression estimators. the LinkedIn gleaned location specification was more informative. This is even more striking finding when considering that the data does not have results for team grouping location on 119 cases. It is within prudence to state that the team location variable has higher informativeness than the domicile location variable, and it may be used for improved prediction of ICO long term performances. Moreover, as indicated by columns 6 and 7 in table 7, the team location, as gleaned from LinkedIn, can also be a better predictor of the asset raise success. Further study is encouraged in domicile, jurisdiction and team location impact. This study mainly utilises these location variables as control variables to measure and assess the significance of network effects.

When further inspecting the regressions' coefficients across all the 9 specifications explaining the log USD million assets raised in table 7, there are evidenced indication of the effects emitting from the project transparency, teams' online presence and professional networks. The specifications 2 and 3 findings corroborate with Howell et al. (2019) transparency's contribution to the ICO asset raising success with ICO organisations reporting data.

Table 7

ICO assets raised in the log millions of US dollars and variable relationships

This table presents estimates from OSL linear regressions of the logarithm of assets raised by the ICO in USD millions. The specification in column 7 contains the Domicile country information and that in Column 8 incorporates the LinkedIn team information, respectively. The results will not show less than 5% significant coefficients for countries of domicile or team location fixed effects the complete list country/regions can be seen in table 3 and 4. For the specifications in columns 1-6, robust standard errors are d shown in brackets. For the specifications of columns 7-8, the standard errors are clustered at the level of ICO end date quarter of years. The asterisks denote the following levels of significance: ***<0.01, **<0.05 and *<0.10.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Own Blockchain	0.350		–	–	–	–	–	–	–
	[0.838]								
LinkedIn reporting dummy	–	0.417**							
		[0.181]							
Domicile reporting dummy	–	–	1.456**	–	–	–	–	–	–
			[0.608]						
Team Reporting dummy	–	–	0.999***	–	–	–	–	–	–
			[0.306]						
Log (# LinkedIn team contacts)	–	–	–	0.167***	–	–	0.154***	0.152**	0.139**
				[0.052]			[0.053]	(0.064)	(0.057)
Number of team members	–	–	–	–	0.030	–	0.007	–	–
					[0.032]		[0.036]		
Team member male	–	–	–	–	-0.001	–	-0.013	–	–
					[0.044]		[0.042]		
Advisory dummy	–	–	–	–	-0.015	–	–	–	–
					[0.136]				
Abandoned LinkedIn profile	–	–	–	–	–	0.16***	0.154***	0.123***	0.094**
						[0.049]	[0.049]	[0.045]	[0.037]
Log (Tokens for sale)	–	–	–	–	–	–	–	0.232***	0.355***
								[0.080]	[0.072]
Log (Price ICO USD)	–	–	–	–	–	–	–	0.189**	0.263***
								[0.083]	[0.080]
ICO end date by quarter	–	–	–	–	–	–	–	-0.054	-0.100**
								[0.055]	[0.040]
Location	–								
Domicile: Bulgaria		–	–	–	–	–	–	-3.132***	–
	–							[0.365]	
Domicile: Estonia		–	–	–	–	–	–	-1.157***	–
	–							[0.375]	
Domicile: Other EU		–	–	–	–	–	–	-1.453***	–
	–							[0.451]	
Domicile: Latvia		–	–	–	–	–	–	-2.179***	–
								[0.242]	
Domicile: Malaysia	–	–	–	–	–	–	–	-1.076***	–
								[0.199]	
Domicile: Malta	–	–	–	–	–	–	–	-1.283***	–
								[0.255]	
Domicile: Russia	–	–	–	–	–	–	–	-0.672**	–
								[0.305]	
Domicile: Seychelles	–	–	–	–	–	–	–	-0.413**	–
								[0.197]	
Domicile: Singapore	–	–	–	–	–	–	–	-0.588**	–
								[0.290]	
Domicile: Ukraine	–	–	–	–	–	–	–	-1.854***	–
								[0.214]	
LinkedIn team: Africa	–	–	–	–	–	–	–	–	3.119***
									[0.452]

Table 7 continued in next page

Table 7 continued from the previous page

LinkedIn team: Brazil	–	–	–	–	–	–	–	–	-0.821***
									[0.289]
LinkedIn team: Bulgaria	–	–	–	–	–	–	–	–	-1.452**
									[0.611]
LinkedIn team: Latvia	–	–	–	–	–	–	–	–	-3.111***
									[0.249]
LinkedIn team: Other America	–	–	–	–	–	–	–	–	-1.982***
									[0.240]
LinkedIn team: Philippines	–	–	–	–	–	–	–	–	-1.744***
									[0.262]
LinkedIn team: Russia	–	–	–	–	–	–	–	–	-0.656**
									[0.287]
LinkedIn team: South Korea	–	–	–	–	–	–	–	–	-0.934**
									[0.469]
LinkedIn team: Spain	–	–	–	–	–	–	–	–	1.123***
									[0.276]
LinkedIn team: Switzerland	–	–	–	–	–	–	–	–	-0.844***
									[0.290]
LinkedIn team: Ukraine	–	–	–	–	–	–	–	–	-1.023***
									[0.359]
LinkedIn team: USA		–	–	–	–	–	–	–	-0.587**
	–								[0.272]
LinkedIn team: UK		–	–	–	–	–	–	REF	REF
R^2	0.002	0.016	0.079	0.030	0.015	0.019	0.053	0.325	0.390
Adjusted R^2	0.000	0.014	0.075	0.027	0.008	0.017	0.042	0.194	0.256
# Observations	469	469	469	350	433	433	350	245	245

When analysing the results in specifications 4, 7, 8 and 9 we can see a positive impact of the higher team log LinkedIn contacts to asset raise with high to moderate significance at over 1.39% effect by a 10% increase in LinkedIn contacts. Interestingly, when the long-term success was analysed, as shown in table 5 and 5.6, there was a reverse negative effect induced by the log team's LinkedIn connections. This is contrary to the findings of Benedetti and Kostovetsky (2018), however, it is important to note that their inspected ICO price development period after the ICO listing on an exchange is 30 days and that their sample's averaged days to the listing of an ICO is 30.5 days. This is comparatively a short-term price performance period. The business contact networks are shown to be valuable, but they may also require resources to be maintained. Possibly by other types of human capital compared to the product/service delivery task related skills.

The number of later abandoned LinkedIn profiles by teams have a strongly significant and positive effect of 16% to the asset raise as shown in specification 3 when solely regressed against the log USD millions assets raised. These specifications were controlled with country fixed effects based on the ICO reported domicile and LinkedIn core team location. The UK was used as the reference variable.

There is no significant effect by whether the ICO organisation had reported having an advisor on ICObench. The advisory indicator variable, as reported by the ICO organisations in the ICObench database, had no significant effect on the ICOs assets raised as tested in specification 4 in table 7. This variable was similarly shown to be informationally redundant for the ICOs' long-term success as evidenced in the specification 11 in table 5. The presumption is that advisors may not be financially compensated and may be lowly incentivised for their activity and thus their contribution to the ICOs remains relatively small. The ICO organisations are human capital intensive with requiring large amounts of development and human hours.

Both 7 and 8 specifications in table 7 use the UK as the reference country variable. Comparing these two specifications separately, the team location variable provides higher explanatory power with higher regression goodness fit with the adjusted R^2 of 0.321 to 0.351 for the applied domicile control variable only. In this respect, the country location of the core team members variable set explains more in the asset raise than the ICO domicile. This may imply that the domicile can be arbitrarily assigned without any legal entity in the jurisdiction or connected to a possible company filing that could be offshore and remote from the team. Contrastingly, the LinkedIn team location variable may be a better indicator of teams' human capital, experience, motivations and incentives, and furthermore, the team members may be physically closer to the investor networks. The proposed latter explanation relates to a well-reported phenomenon of investor bias toward regional or familiar investment opportunities (e.g. Kilka and Weber, 2000; Feldstein and Horioka, 1980).

The domicile location effect to the log USD in millions raised on specification 7 is negative in all cases when compared to the UK. Bulgaria at -312%, Latvia at -218% and Ukraine at -185% showed to have the largest and highly significant negative effects on the asset raise in comparison to the UK. This might be due to their comparatively lower national GDP and the availability of funds to invest. Interestingly, Other EU countries that include ICOs from Austria, Belgium, Finland, Italy, Luxembourg, Portugal, Romania and Sweden, also show a highly significant negative effect at -145% by the location domicile. This could be about the investors' lack of interest in ICO projects and the existence of other available investment opportunities. Furthermore, the country comparisons were conducted naïvely, e.g. without PPP or GDP adjustments.

Of the team location, as estimated from the constructed team LinkedIn profile variables in specification 8; Africa, which contains countries such as Kenya, Nigeria and Tanzania have a highly significant 319% effect. Also, the results for Spain show a highly significant positive effect at 112% for the asset raise compared to the UK. The largest negative effects for asset raise by LinkedIn team location countries were Latvia at -308%, the Philippines at -196% and Ukraine at -104% with the highest level of significance. Interestingly, the US shows a moderately significant negative effect of -57% when compared to the UK.

Intuitively, log Token Price in USD and log Token for Sale have a significantly positive relation with raising ICO (log) assets. Raiaws. A 1% increase in log Token Price in USD contributes towards an increase of 37.3% in the raising ICO log assets in millions of US dollars. This is similar for log Token for Sale. The larger issuances may be anticipated to provide a more scalable market solution, for example, compared to bitcoin's pre-set limit of 21 million coins. When the bitcoin price has increased, so have the transaction fees on that blockchain. Higher token issuance numbers may also provide support for the 'lottery feature' which can attribute to the ICO performance, as here the tokens are low in absolute price at ICO (Fahlenbrach and Frattaroli, 2019). The sample's median token price is 0.14 USD with the lowest being 0.0001 USD.

5. Conclusion

This study examines the role of technology and network effects in the long-term performance of ICOs. The findings suggest that entailing own proprietary blockchain has a large effect on the long-term success of an ICO compared to only to the amount of assets raised. This phenomenon can be explained as the present network effect. In addition, the cointegration to the existing platform or digital currency such as ether has a large negative effect on the ICO's long-run success. Whilst the projects may have been able to raise funding, the initiatives may yet to be produced and exhibit proprietary innovation with showing low intrinsic value. Both network effects and cointegration were seen to show significant results against here proposed Modified Information Ratio that introduced as the measuring tool to assess ICOs in this study.

The impact of the network effects may be considered to have fundamental value, which is widely discussed as being absent in the crypto assets. The ICO is an innovative fundraising method to raise funds for digital organisations for which this otherwise remains to be challenging. Auxiliary findings corroborate the organisational transparency factor to the ICO asset raising success, but also that the higher number of online business connections contributes positively to the ICO asset raise. However, the higher amount of business connections by the team members do not translate to a positive effect on the long-term success of an ICO, but reverse. This has implications on ICOs management of resources planning. Noting that the ICOs may only have used a platform such as ethereum to issue tradable tokens to facilitate their fund raising. The sponsoring of undeveloped goods will not expectedly create real network effects, but conversely, the ICO asset raise onto existing blockchain will show network effects due to its utility to users and the added externality. The existence of network effects factor is also important for an investor, as there was no indication of investor preference over whether the ICO organisation had already their own proprietary blockchain. The own proprietary blockchain had no impact on long-term performance either until it was interacted with ICO assets raised. In this sense, the technology enabled the network effect formation.

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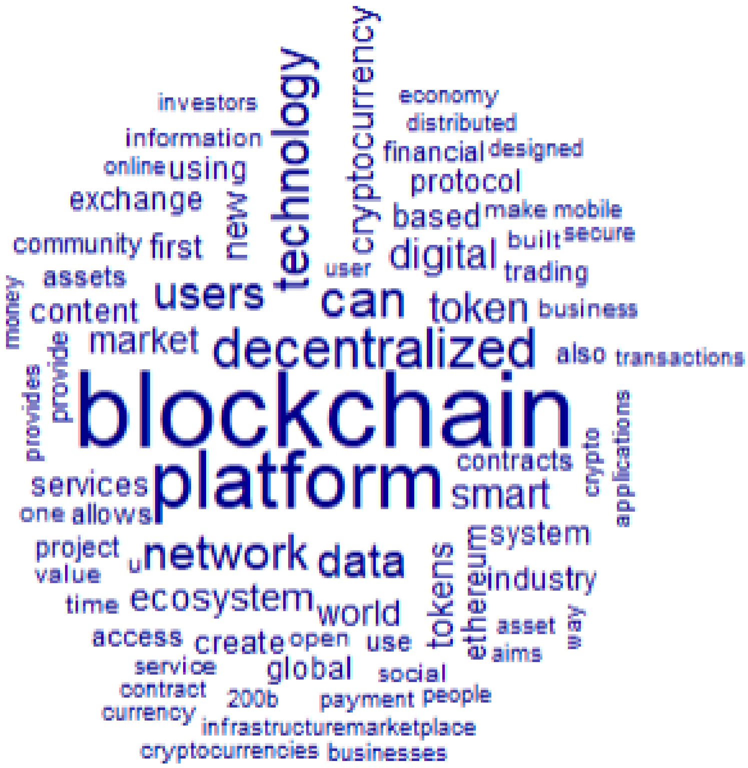
Appendix 1

Figure 1.

Frequency display of words extracted on ICOs



Key words in the ICO introduction	N	%
Blockchain	488	72%
Platform	362	54%
Decentralized	223	33%
Technology	196	29%
Network	187	28%
Data	179	27%
Users	176	26%
Token	166	25%
Digital	149	22%
Smart	144	21%

The features are taken from the ICO introductions. The percentage is computed from the total observation number of 675 ICO sample.

Figure 2.
Frequency display of Male occupational title words

Key words in the occupational title	N	%
Developer	660	11%
Co-Founder	502	9%
CEO	468	8%
Engineer	364	6%
Blockchain	363	6%
Founder	327	6%
Manager	317	5%
Director	285	5%
Chief	255	4%
Lead	254	4%

The percentages are computed from 5,346 male team member sample.

Figure 3.
Frequency display of Female occupational title words

Key Words in the occupational title	N	%
Manager	161	16%
Marketing	91	9%
Head	66	7%
Director	60	6%
Co-founder	59	6%
Developer	49	5%
Community	45	4%
Business	40	4%
Designer	38	4%
Development	36	4%

The percentages are computed from 1,001 female team member sample.

Appendix 2
Co-integration test

1. Testing for the Unit Root

The ICO -, ethereum - and bitcoin log-transformed daily price timeseries are tested separately for a unit root at 1% significance. Then Augmented Dickey-Fuller test is applied with fixed lags of 2, as there were 675 individual ICOs to test and the use of e.g. the Akaike information criterion (Akaike, 1969, 1971 and 1974) (hereafter AIC) would produce differing lags. This could make the results more complex to compare as the ICO's time periods are different.

The individual tests results show that unit root is present with 609 ICO -, ethereum - and bitcoin timeseries. The rest of the ICO sample [N:66], which do not exhibit a unit root, is ignored.

2. Testing for the Cointegration

Johansen's cointegration eigenvalue test (Johansen, 1988) is then employed to 609 non-stationary ICO daily timeseries with ethereum and separately with bitcoin at 5 % significance. The Johansen eigenvalue test was used as for its comparably higher robustness over the Johansen trace test in treating smaller samples (Lütkepohl, et al. 2001). Whilst the mean trading day is 536 days, the standard deviation is 270 days. The trend is also applied here due to the ICO sample's mean annualised return of -248%. The AIC is used to determine the lag length for the ICO and ethereum or bitcoin cointegration test with a maximum lag set to 20. The test statistics are compared with the critical values drawn from Juselius (2006). The results show that 100 ICOs have a cointegration relationship with ethereum and, separately, 86 ICOs present a cointegration relationship with bitcoin at 5% significance.

The results are made into dummy variables for all the ICOs observations [N:675].