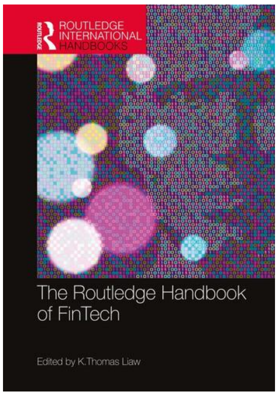
This article was downloaded by: *10.2.97.136*
On: 24 Mar 2023
Access details: *subscription number*
Publisher: *Routledge*
Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: 5 Howick Place, London SW1P 1WG, UK



The Routledge Handbook of FinTech

K. Thomas

Initial coin offerings

Publication details
https://test.routledgehandbooks.com/doi/10.4324/9780429292903-9
Paola Cerchiello, Anca Mirela Toma
Published online on: 15 Jun 2021

How to cite :- Paola Cerchiello, Anca Mirela Toma. 15 Jun 2021, *Initial coin offerings from:* The Routledge Handbook of FinTech Routledge
Accessed on: 24 Mar 2023
https://test.routledgehandbooks.com/doi/10.4324/9780429292903-9

PLEASE SCROLL DOWN FOR DOCUMENT

Full terms and conditions of use: https://test.routledgehandbooks.com/legal-notices/terms

This Document PDF may be used for research, teaching and private study purposes. Any substantial or systematic reproductions, re-distribution, re-selling, loan or sub-licensing, systematic supply or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The publisher shall not be liable for an loss, actions, claims, proceedings, demand or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

7

INITIAL COIN OFFERINGS

A statistical analysis of the main characteristics

Paola Cerchiello and Anca Mirela Toma

1 Initial coin offerings

Initial coin offerings (ICOs) became famous as the finance model of cryptocurrencies. They are a digital way of public capital funding for entrepreneurial use through the issue of an own virtual token [1]. A token is a 'cryptographically' secured digital asset' ([2], p.2). For companies whose business model stands in connection with blockchain technology, ICOs have surpassed the traditional venture capital financing in the shortest of time [3]. This means that ICOs are a new way to raise capital for young and unestablished ventures.

The first ICO was held in July 2013 by Mastercoin, which is a digital currency built on the Bitcoin blockchain [4]. Since then, over 1,000 ICOs have followed. CoinSchedule, a leading website monitoring current ICOs, reports that 366 ICOs took place in 2017, raising a combined amount of USD 6.2 bn. According to Fisch [5], the aggregated 2017 funding volume was surpassed in the first three months of 2018 alone; 254 ICOs raised USD 7.8 bn in this period. The premier crowdfunding platform Kickstarter in contrast has raised a total of USD 4.6 bn since its inception in 2009 [6]. In the month of June 2018 alone, the ICO funds raised the amount to over USD 5 bn with 91 ICOs ending in that period. However, since then, monthly funds raised remained more or less distinctly under the mark of USD 1 bn except for May 2019. The number of token sales has also declined from the staggering number of 146 ended ICOs at the maximum in April 2018 to four ended token sales in September 2019 [7].

It is to be noted that an officially recognized definition of ICOs does not exist [1]. The name initial coin offering is a reference to the well-established concept of initial public offerings (IPOs). However, at first sight, ICOs have relatively few things in common with traditional public offerings. Through an ICO, a new firm offers a token to a crowd of investors for the first time. In IPOs the company is most often already established and has had rather a successful past. In an IPO, shares of the company are sold. In an ICO, the sold token is created by the firm offering it using distributed ledger technology (DLT) and can be bought in exchange for at money or other cryptocurrencies. The functions of the token may equal classical shares but are manifold [8].

The spike in the occurrence of ICOs followed the development of the Blockchain by Nakamoto in 2008 and the subsequent development of cryptocurrencies such as Ethereum (short: ether) [9]. A blockchain enables the direct, secure transfer of value over the Internet

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

between parties that do not trust each other [2]. It consists of a sequential list of transactions in a unit of value that is native to the blockchain. For example, the Bitcoin blockchain uses the cryptocurrency bitcoin and the Ethereum blockchain uses ether. Additional text, such as contingent terms of contracts, can be appended to a transaction. Bitcoin permits simple and limited additional text, whilst other blockchains such as Ethereum essentially permit any code to be executed as part of a transaction. Blockchains are so-called distributed ledgers, providing decentralized record-keeping that cannot be retroactively edited. Cryptography enables rapid verification and prevents hacking [2]. Distributed ledger technology (DLT) describes a decentralized database stored on a set of individual nodes. The records are synchronized through a consensus algorithm, which allows peer-to-peer transactions without the need for an intermediary. This is the technical basis of an ICO in various forms [1]. The token sales themselves are conducted via complex, self-enforcing and state-contingent smart contracts, which are pieces of code embedded in a blockchain. This enables the exchange of money, property or other assets without an intermediate party. Smart contracts guarantee the fulfilment of the transaction and regulate for example the conditions of sale for the tokens [1]. Therefore, due to low transaction costs similar to crowdfunding, ICOs might become a significant driver for financial inclusion by democratizing access to investments and capital [10].

Recently, there has been a growing literature studying the ICOs drivers aiming to predict their future outcome. A study by [1] offers an exploratory empiric classification of ICOs and the dynamics of voluntary disclosures. It examines to what extent the availability and quality of the information disclosed can explain the characteristics of success and failure among ICOs and the corresponding projects. Another important research focuses on the effectiveness of signalling ventures and ICO projects' technological capabilities to attract higher amounts of funding [5].

Other streams of research concentrate on the impact of managers quality on the ICOs. Momtaz (2019) studies the impact of CEOs' loyalty disposition and the magnitude of asymmetry of information between managers and investors on ICOs' performance [11]. Moreover, to remain in the management area, an interesting spark comes from research specifically directed at CEOs' roles and effects on ICO results [12]. Finally, another area of study focuses on the driving factors impacting the liquidity and trading volume of crypto-tokens listed after the ICOs. Identified among these factors have been the quality level of disclosed documentation (source code public on GitHub white paper published, an intended budget published for use of proceeds), the community engagement (measured by the number of Telegram group members), the level of preparation of the management (using as proxy the entrepreneurial professional background of the lead founder or CEO), and other outcomes of interest (i.e., the amount raised in the ICO, outright failure – delisting or disappearance, abnormal returns, and volatility) [2].

Despite the interest created by ICOs and the constantly growing trends, it is worth mentioning that almost half of ICOs sold in 2017 had failed by February 2018. What should drive more attention to ICOs is the consistent presence of scam activities only devoted to fraudulently raising money. According to Cointelegraph, the Ethereum network (the prevalent blockchain platform for ICOs) has experienced considerable phishing, Ponzi schemes, and other scam events, accounting for about 10% of ICOs. On the other hand, it is interesting to assess which factors affect the probability of success of an ICO. Adhami et al. in 2018, based on the analysis of 253 ICOs, showed that the following characteristics contribute: the availability of the code source, the organization of a token pre-sale and the possibility for contributors to access to a specific service (or to share profits)[13].

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

The main source of information about blockchain, tokens and ICOs is the Web. Here we can find sites enabling exploration of the various blockchains associated with the main cryptocurrencies, including Ethereum's. We can also find websites giving extensive financial information on prices of all the main cryptocurrencies and tokens, sites specialized in listing the existing ICOs and giving information about them. Often, these sites evaluate the soundness and likelihood of success of the listed ICOs. One of the most popular among these sites is icobench.com, which evaluates all the listed ICOs and provides an API (Application Programming Interface) to automatically gather information on them. ICOs are usually characterized by the following features: a business idea, most of the time explained in a white paper, a proposed team, a target sum to be collected, a given number of tokens to be given to subscribers according to a predetermined exchange rate with one or more existing cryptocurrencies. Nowadays, a high percentage of ICOs are managed through Smart Contracts running on Ethereum blockchain, and in particular through ERC-20 Token Standard Contract [14].

On top of all the characteristics explained so far, there is a further and not yet explored point of interest: the Telegram chats. Telegram is a cloud-based instant messaging and voice over IP service developed by Telegram Messenger founded by the Russian entrepreneur Pavel Durov. In March 2018, Telegram stated that it has 200 million monthly active users – "This is an insane number by any standards. If Telegram were a country, it would have been the sixth-largest country in the world" (Telegram, 2018). Telegram is completely free and has no ads, users can send any kind of media or documents and can program messages to self-destruct after a certain period. Some characteristics are imposing Telegram among the first social networks; indeed it intentionally does not collect data about where its clients live and what they use the platform for. This is one of the main reasons why, according to AppAnnie rankings, Telegram is particularly popular in countries like Uzbekistan, Ukraine, and Russia, where Internet access may be limited or closely monitored by the government. As of October 2017, Telegram was by far the most popular offcial discussion platform for current and upcoming ICOs, with 75%+ of these projects employing it. This means that retrieving Telegram discussions associated with each and every ICO would produce a huge amount of textual information potentially useful for understanding the chance of success and more interestingly possible signs of fraudulent activities.

In this chapter, we explain how to leverage two kinds of information: structured and unstructured ones. Regarding the former, we take advantage of classical statistical classification models to distinguish the status of an ICO that is made up of two classes, intended as follows:

- Success = 1: the ICO collects the predefined hard cap within the time horizon of the campaign;
- Failure/scam = 0: the ICO does not collect the predefined hard cap within the time horizon of the campaign.

Logistic regression aims at classifying the dependent variable into two groups characterized by a different status [1=scam vs 0=success or 1=success vs 0=failure] according to the following model:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \alpha + \sum_j \beta_j x_{ij} \quad (1)$$

where p_i is the probability of the event of interest, for ICO i, $x_i = (x_{i1},\ldots, x_{ij},\ldots, x_{iJ})$ is a vector of ICOs specific explanatory variables, the intercept parameter, as well as the regression

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

coefficients$_j$, for j = 1; :::; J, are to be estimated from the available data. It follows that the probability of success (or scam) can be obtained as:

$$p_i = \frac{1}{1+\exp(\alpha+\sum_j \beta_j x_{ij})} \quad (2)$$

Since the target variable is naturally categorized according to three classes, success, failure and scam we extend the aforementioned binary logistic regression to a multinomial one. Such model assesses all the categories of interest at the same time as follows:

$$\ln\left(\frac{p_k}{1-p_k}\right) = \alpha_k + \sum_j \beta_k x_{ij} \quad (3)$$

where p_k is the probability of kth class for k = 1;…… K given the constraint P that $\sum_k p_k = 1$.

Considering the textual analysis of Telegram chats, we take advantage of the quantitative analysis of human languages to discover common features of written text. In particular, the analysis of relatively short text messages like those appearing on the micro-blogging platform presents several challenges. Some of these are the informal conversation (e.g. slang words, repeated letters, emoticons) and the level of implied knowledge necessary to understand the topics of discussion. Moreover, it is important to consider the high level of noise contained in the chats, witnessed by the fact that only a fraction of them with respect to the total number available is employed in our sentiment analysis.

We have applied a Bag of Word (BoW) approach, according to which a text is represented as an unordered collection of words, considering only their counts in each comment of the chat. The word and document vectorization has been carried out by collecting all the word frequencies in a Term Document Matrix (TDM). Afterwards, such matrix has been weighted by employing the popular TF-IDF (Term Frequency Inverse Document Frequency) algorithm. Classical text cleaning procedures have been put in places like stop-words, punctuation, unnecessary symbols and space removal, specific topic words addition. For descriptive purposes, we have used word-clouds for every Telegram chat according to the general content and to specific subcategories like sentiments and expressed moods. The most critical part of the analysis relies on sentiment classification. In general, two different approaches can be used:

- Score dictionary-based: the sentiment score is based on the number of matches between a predefined list of positive and negative words and terms contained in each text source (a tweet, a sentence, a whole paragraph);
- Score classifier-based: a proper statistical classifier is trained on a large enough dataset of pre-labelled examples and then used to predict the sentiment class of a new example.

However, the second option is rarely feasible because to be a good classifier, a large amount of pre-classified examples are needed and this represents a particularly complicated task when dealing with short and extremely non-conventional text like micro-blogging chats. Therefore, we decided to focus on a dictionary-based approach, adapting appropriate lists of positive and negative words relevant to ICO topics in the English language.

The lexicons used are based on unigrams, i.e., single words; they contain many English words and the words are labelled with scores for positive/negative sentiment and also possibly emotions like joy, anger, sadness, and so forth. Among the possible vocabularies, we consider the following ones: NRC, BING and AFINN. The NRC lexicon categorizes words in a binary fashion (yes/no) into categories of positive, negative, anger, anticipation,

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

disgust, fear, joy, sadness, surprise, and trust. The BING lexicon categorizes words into a binary manner into positive and negative categories. The AFINN lexicon assigns words with a score that runs between -5 and +5, with negative scores indicating negative sentiment and positive scores indicating positive sentiment. By applying the above lexicons, we produce for every ICO a sentiment score as well as counts for positive and negative words. All these indexes are used as additional predictors within the logistic models.

2 Data

As already mentioned, we exploit structured and unstructured information and empirically examine 195 ICOs starting from January 2017 till November 2018.

The first step in collecting data about each project is to gather information from the most used ICO related platforms such as Icobench, TokenData, Coinschedule or similar. During this phase, we look for general characteristics such as the name, the token symbol, start and end dates of the crowdfunding, the country of origin, financial data such as the total number of tokens issued, the initial price of the token, the platform used, data on the team proposing the ICO, data on the advisory board, data on the availability of the website, availability of white paper, white-paper characteristics, and social channels.

Some of these data, such as short and long description, and milestones are textual descriptions. Others are categorical variables, such as the country, the platform, the category (which can assume many values), and variables related to the team members (name, role, group). The remaining variables are numeric, with different degrees of discretization.

As concerns the unstructured data, insightful information can be derived from the white papers in terms of quality of the technical report and specific content. A white paper is a summary report that provides detailed information about the project, its originality and the benefits available to investors and users, the technological features, the team behind the project, the project's background and plans. The dimensions captured through the white paper features consist in checking the availability of the document for the ICO in question and additional information about its scope (pages, sections, appendix). Furthermore, data on the disclosure of information regarding the issuers were collected (names and/or photographs of issuing and advising team members).

Social channels are more personal than every database, rating platform or website, so they are a way to reach a wide range of users, to update them constantly about the evolution of the project and in the end to create a trusted environment that can finalize in successful crowdfunding activity. To conduct the textual analysis, we enrich our database with the social channels data, such as the presence of a channel, the numbers of users as a proxy of the community engagement and as mentioned in the introduction the textual chat, retrieved backwards till the creation of the chat, used to produce a sentiment-based score for every ICO.

In Table 7.1 we report the complete list of collected and employed variables.

3 Empirical evidence

In this section, we report our main results obtained from classification and textual analysis. In Table 7.2 and Table 7.4 we report results respectively for logistic regression on Success/Failure (class 2 variable) and multi logit regression estimated on failure (f) and scam (sc) compared to success as the baseline. Regarding the first model, in Table 7.2 we report the final configuration after several stepwise selection steps. The reader can see that the only two relevant dummy variables are: the presence of a white paper (Paper du) and a Twitter account

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

Table 7.1 Explanatory variables

Class0	f = failed, sc= scam, su= success
Class1	0 = scam 1 = failed+ success
Class2	0 = failed 1 = success
W_Site	Website (dummy)
Tm	Telegram
W_Paper	*White paper (dummy)*
Usd	Presale price in USD
Tw	Twitter (dummy)
Fb	Facebook (dummy)
Ln	LinkedIn (dummy)
Yt	YouTube (dummy)
Gith	GitHub (dummy)
Slack	Slack(dummy)
Reddit	Reddit (dummy)
Btalk	Bitcoin talk (dummy)
Mm	Medium (dummy)
Nr_Team	Number of Team members (quantitative)
Nr Adv	Number of advisors (quantitative)
Adv	Existence of advisors (dummy)
Project	name of the ICO (categorical)
Nr Tm	Number of users in Telegram (quantitative)
Tot Token	Number of Total Tokens (quantitative)
Pos Bing Standardized	no. of positive words for BL list (quantitative)
Neg Bing Standardized	no. of negative words for BL list (quantitative
Pos NRC Standardized	no. of positive words for NRC list (quantitative)
Neg NRC Standardized	no. of negative words for NRC list (quantitative)
Sent NRC Standardized	sentiment for NRC list (quantitative)

(tw). Both present positive coefficients showing their impact on increasing the probability of success of an ICO. It should be stressed that the influence of Twitter channel is much higher than the presence of a white paper, indeed if we calculate the associated odds ratio we would get respectively 11.94 and 3.85. In other words, if the ICO has a Twitter account the probability of success is almost 12 times higher (almost four times higher for the white paper). Regarding the three continuous variables, number of elements of the team (Nr team), number of advisors (Nr adv) and scaled sentiment score based on NRC lexicon (Sent NRC sc), they are all highly significant and again positive suggesting that increasing people and advisors in the team has a positive impact. Regarding the sentiment, we notice a particularly high positive value, stressing the importance of the perception of possible investors who interact with the ICO proposer by means of a social media, namely Telegram.

To further evaluate such configuration, we have explored the VIF index (Table 7.3) that accounts for the level of multicollinearity brought by every variable. The VIF results for the two model configurations are reported in Table 7.3 (logistic) and 7.5 (multinomial), with useful insights in defining the lack of multicollinearity. Therefore in Table 7.3, we can see low values for the VIF index associated with the estimated logistic model (given in Table 7.2). The reader can easily notice that there is not any multicollinearity effect, making the model robust. Moreover, reported performance indexes, namely AIC and pseudo R^2, present good values above 50%.

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

Table 7.2 Logistic regression results on success/failure ICOs

	Dependent variable
	Class 2
Tw	2.481*
	(1.381)
Paper_du	1.351**
	(0.635)
Nr_adv	0.461***
	(0.135)
Nr_team	0.233⋆
	(0.088)
Sent_NRC_sc	0.233⋆
	(0.088)
Constant	0.233⋆
	(0.088)
Observations	196
Akaike Inf Crit	89.41
McFadden pseudo R2	0.63
McFadden Adj. pseudo R2	0.57
Cox & Snell pseudo R2	0.49

Note ⋆p<0.1; p<0.05; ⋆p<0.01

Table 7.3 VIF index for logistic regression model

Tw	*Paper du*	*Nr Adv*	*Nr Team*	*Sent NRC sc*
1.229	1.033	1.067	1.053	1.228

In Table 7.4, we report results for fraudulent and scam ICOs compared to successful ones, based on a multilogit regression. Looking at the estimated parameters, we can infer that the patterns are different. The presence of a website has a positive impact on the probability of being a successful ICO and not a scam. In other words, the absence of this characteristic is a driver of scam activity suspects. Instead, the website does not differentiate successes from failures. With regards to the presence of advisors and of a white paper, both the variables are significant in differentiating fraudulent from successful ICOs, confirming the results of logistic regression. There is no statistical significance for fraudulent ICOs. Lastly, the variable on the sentiment score is relevant and with a negative sign for both the classes; in other words, an increase in the sentiment causes an increase in the probability of success when we consider both failed and fraudulent ICOs.

In this regard, we should stress that the incidence of scam ICOs in our database is extremely low; the reason being that collecting information about such ICOs is particularly complex. Most of the information is completely deleted from the Web as soon as the activity is recognized as illegal and/or fraudulent. The overall model performance, assessed again in terms of AIC and pseudo R^2, is pretty good although inferior to the previous one.

In Table 7.5 we also report VIF index, to check the absence of multicollinearity in the reported model. Please note that multilogit model reported in Table 7.4 is a final configuration obtained through stepwise selection.

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

Table 7.4 Results from multilogit regression: failure and scam compared to success

	Dependent variable	
	Sc = scam (1)	*f =failed* (2)
Oweb dum	−1.962	0.093
	(0.977)	(0.773)
Adv_dum	−0.899	−1.707***
	(0.809)	(0.571)
Paper du	−0.728	2.158***
	(0.915)	(0.657)
Sent NRC	−1.390	−2.606*
Constant	−0.628	−0.572
	(0.997)	(0.925)
Akaike Inf Crit	166.339	166.339
Pseudo R square	McFadden 0.43- McFadden Adj. 0.36- Cox & Snell 0.44	

Note *$p<0.1$; $p<0.05$; *$p<0.01$

Table 7.5 VIF index for multilogit regression model

Oweb dum	*adv dum*	*Paper du*	*Sent NRC sc*
3.656	2.317	3.607	3.870

4 Discussion and conclusions

Initial coin offerings are one of the several by-products of the world of cryptocurrencies. Start-ups and existing businesses are turning to alternative sources of capital as opposed to classical channels like banks or venture capitalists. They can increase the inner value of their business by selling tokens, i.e. units of the chosen cryptocurrency. The investors, of course, hope for an increase in the value of the token in the short term, provided there isa solid and valid business idea typically described by the ICO issuers in a white paper. However, fraudulent activities perpetrated by unscrupulous actors are frequent and it is crucial to highlight in advance clear signs of illegal money raising.

In this perspective, analysis of ICOs can be considered a very particular type of fraud detection activity. However, in our opinion fraud detection presents some specificity that prevents us from entailing ICOs related problems as a proper instance of fraud detection. In particular, our data are not owing in such huge amount from an on-line system as typically happens with credit card payments or banks transactions. Typical fraud detection approaches, as in Maheshwara et al. (2019), aim at discovering, almost in real times, fraudulent financial activities based on transactional data that ideally should be blocked as soon as possible. ICOs instead are characterized by a slow process of engagement of the prospective clients and establishment of consensus that goes through Telegram chats (if available), white paper and website. That being the case, we would suggest labelling this specific stream of research as FinTech Fraud detection with all the relative specificity [15].

While analyzing the success vs failure dynamic with a classification model is relatively easy since the incidence of the two classes is almost equal (50-50), it is much more complicated to highlight the key aspects that could witness a fraudulent activity since 2017, only a

Downloaded By: 10.2.97.136 At: 16:35 24 Mar 2023; For: 9780429292903, chapter7, 10.4324/9780429292903-9

few scam events have been reported. In our sample of 196 ICOs (data collection still active), there are 10 scam ICOs and we fit a multilogit regression model for comparing scam and failed ICOs towards successful ones. Results tell us that the presence of a website has a positive impact on the probability of not being a scam but does not have any impact on failed ones. In terms of sentiment expressed on Telegram chats, the impact appears to be negative both on the scam and failed ICOs. This suggests that monitoring in real-time Telegram chats could represent a valid means for collecting signs of possible problems within the ICOs. If instead, we compare successful ICOs against failed ones, we noticed that the presence of a White Paper and a Twitter account show positive coefficients.

Regarding the three continuous variables – number of elements of the team, number of advisors and sentiment score based on NRC lexicon – all are highly significant and positive suggesting that increasing the number of people in the team and the number of advisors has a positive impact. Regarding the sentiment, we notice a particularly high positive value, stressing the importance of the perception of possible investors who interact with the ICO proposer employing social media.

References

[1] Blaseg, Daniel. (2018). Dynamics of voluntary disclosure in the unregulated market for Initial Coin Offerings. *SSRN Electronic Journal*. 10.2139/ssrn.3207641.

[2] Howell, Sabrina T and Niessner, Marina and Yermack, David (September 3, 2019). Initial Coin Offerings: financing growth with cryptocurrency token sales. European Corporate Governance Institute (ECGI) - Finance Working Paper No. 564/2018, Available at SSRN: https://ssrn.com/abstract=3201259 or http://dx.doi.org/10.2139/ssrn.3201259.

[3] Hahn, Christopher and Wilkens, Robert. (2019). ICO vs. IPO – Prospektrechtliche Anforderungen bei Equity Token Offerings. *Zeitschrift für Bankrecht und Bankwirtschaft*, 31: 10–26. 10.15375/zbb-2019–0104. title in english: ICO vs IPO Prospectus law requirements for Equity Token Offerings.

[4] Shin, Laura. (2017). Here's the man who created ICOs and this is the new token he's backing. *Forbes Online*.

[5] Fisch, Christian. (2019). Initial coin offerings (ICOs) to finance new ventures. *Journal of Business Venturing* 34: 1–22. 10.1016/j.jbusvent.2018.09.007.

[6] Kickstarter. (2019). Kickstarter statistics. Kickstarter (Online).

[7] Coinschedule. (2019). Crypto token sales market statistics. Coinschedule.com.

[8] Catalini, Christian and Gans, Joshua S. (March 5, 2019). Initial Coin Offerings and the value of crypto tokens. *MIT Sloan Research Paper* No. 5347-18, Rotman School of Management Working Paper No. 3137213. Available at SSRN: https://ssrn.com/abstract=3137213 or http://dx.doi.org/10.2139/ssrn.3137213.

[9] Mollick, Ethan and Robb, Alicia. (2016). Democratizing innovation and capital access: the role of crowdfunding. *California Management Review* 58: 72–87. 10.1525/cmr.2016.58.2.72.

[10] Momtaz, P.P. (2020). Initial coin offerings, asymmetric information, and loyal CEOs. *Small Bus Econ*. https://doi.org/10.1007/s11187-020-00335-x.

[11] Momtaz, Paul P. (December 20, 2019). CEO Emotions and underpricing in initial coin offerings. Available at SSRN: https://ssrn.com/abstract=3580719 or http://dx.doi.org/10.2139/ssrn.3580719

[12] Giudici, Giancarlo, Adhami, Saman and Martinazzi, Stefano. (2018). Why do businesses go crypto? An empirical analysis of Initial Coin Offerings. *Journal of Economics and Business* 100. 10.1016/j.jeconbus.2018.04.001.

[13] Fenu, G., Marchesi, L., Marchesi, M. and Tonelli, R. (March, 2018). The ICO phenomenon and its relationships with ethereum smart contract environment. In 2018 International Workshop on Blockchain Oriented Software Engineering (IWBOSE) (pp. 26–32). IEEE.

[14] Sadgali, I., Sael, N. and Benabbou, F. (2019). Performance of machine learning techniques in the detection of financial frauds. *Procedia Computer Science* 148: 45–54.

[15] Maheshwara Reddy, C., B. Marri Saiteja, and Mrs Dhikhi. (2019). Financial fraud detection using machine learning. *IJIRT* 6 (6) ISSN: 2349–6002.