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BLOKŲ GRANDINE GRĮSTA ŽETONŲ EKONOMIKA: PIRMINIO VIEŠOJO KRIPTOVALIUTŲ SIŪLYMO SUTELKTINIO FINANSAVIMO IR ANTRINĖS RINKOS TYRIMAS	**BLOCKCHAIN-BASED TOKEN ECONOMY: ICO CROWDFUNDING AND POST-ICO MARKET PERFORMANCE**

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GLOSSARY

DAO - Decentralized Autonomous Organization

DApp – decentralized applications

ICO – Initial Coin Offerings

Cryptography – a method of transmitting data in a particular form that not all can read and process it;

Blockchain – open-source system or public distributed ledger

Mining – the process within cryptocurrencies are added to the network;

Altcoins – all other cryptocurrencies, excluding Bitcoin;

Fiat currency – money established under the government regulation;

FINMA - Swiss Financial Market Supervisory Authority;

SEC – US Securities Exchange Commission;

DApps - Decentralized digital applications that exist on a blockchain;

VC – Venture Capitalists.

INTRODUCTION

Since Bitcoin was first introduced by Nakamoto in early 2009, cryptocurrencies and blockchain has increasingly occupied great importance of nowadays-financial market. Therefore, cryptocurrencies are no longer an absolute novelty whereas the market capitalization of digital coins has skyrocketed and public awareness has increased significantly. Not only the investors has great interest into virtual currencies, but also the national governments and yet policy-makers such as U.S. Securities and Exchange commission, European Securities and Markets Authority, etc. The prevalence of improved blockchain and cryptocurrencies has foster the growth of a new phenomenon, called Initial Coin Offering (ICO), as the new financing instrument for entrepreneurial ventures. Generally, ICO is defined as a decentralized method of funding where blockchain-based organizations issue new tokens (that can be sold online or used in the future to obtain products, services or profits) in exchange to preexisting cryptocurrencies (usually, Bitcoin or Ether) (Adhami et al., 2018; Huang, 2019). ICOs are simply considered as an alternative to already existing methods of funding, for instance, Venture capitalists or conventional crowdfunding. Moreover, major part of ICOs have listing stage, which has attracted high interest from investors.

Although the phenomenon has recently emerged, blockchain-based tokens have already became well known all over the world. Very first ICO was initiated in 2013 by Mastercoin, however, prevalence rapidly accelerated only in 2017. Between 2017 and 2019, ICOs raised over € 13 billion (icodata.io). At least 16 ICOs projects have collected more than € 100 million each (tokendata.io). However, in mid-2019, volumes of ICOs started to decline mostly because of the uncertainty of future requirements. Nevertheless, the occurrence of ICOs provided companies with outright and immediate early-stage crowdfunding, reduced costs and intermediation fees (Fisch et al., 2019, Adhami et al. (2018), eliminated geographical boundaries, and implemented high liquidity for investors (Amsden et al., 2018). The prevalence of ICO brought many benefits to businesses but likewise challenged regulation authorities, entrepreneurs, and investors. Companies initiating token sales could collect vast amounts of money with limited extent of information and without any insurance to participants of the project. Individuals are getting more aware of what features and signals of ICO campaigns are reliable, transparent and expedient (Masiak et al., 2019). Nevertheless, speculators still appear since there is no continuous and common rules applied to token sales market.

The amount of empirical analyses towards token economy is rapidly evolving even though the interest in Initial Coin Offerings is newly arisen. Researchers mostly focus on success factors (Howell, 2020; Chen, 2019; Fisch et al., 2019; Huang et al., 2019; Adhami et al., 2018, etc.), elements of value (Masiak et al., 2019; Felix et al., 2019; Catalini et al., 2018), legal and regulation aspects (An et al., 2018; Zetzsche et al., 2018; Chanson et al., 2018) as well as general overview about the ICO market (Chanson et al., 2018; Corbet et al., 2019). However, there are still left many questions that recent literature is starting to undertake. In year 2020, the most analyzed topic is towards ICO market returns, market efficiency and information asymmetry (Fisch and Momtaz, 2020; Domingo et al., 2020, etc.). However, there is lack implications composed in regards of post-ICO market, value determinants, and pricing. In addition, determination of aspects influencing ICO profitability helps to improve ICO campaign performance, the settlement of success, and market transparency. As tokens in ICO project do not have present value, no pricing mechanisms are applied; it is difficult to estimate the time framework of the profitability of the project. Therefore, this research aspire to answer what creates value for ICOs in crowdfunding stage. ICO originator's issued coins become valuable when network of the campaign matures. Many substantial forces lead to constantly increasing demand for blockchain–based early funding; qualifying attributes causing increased value for tokens is one of the main forces that induces competitive market and incidence of ICO projects. Moreover, post-ICO market has recently significantly expanded and token exchanges became highly popular between participants that are interested in trading altcoins. As there is lack of implications towards secondary market, this research also pursue to ascertain how post-ICO market performs when tokens are listed.

Aim of the research. The purpose of the thesis is to determine which elements have the most influence on ICO gains in crowdfunding stage and to examine post-ICO token market performance.

The main objectives of the research:

1. To examine and distinguish processes of ICO mechanism;
2. To theoretically analyze blockchain-based token market dynamics explored in the literature;
3. To analyze research methods applied in the literature and prepare respective methodology for ICO crowdfunding stage and post-ICO market performance analyses;
4. To investigate the most valued aspects of ICO that cause higher funds in ICOs crowdfunding stage and analyze results;
5. To investigate if post-ICO market performance is influenced by shocks in Bitcoin and Ether markets as well as analyze results;

Research methods. Related researches were gathered and systemized to explore contribution of means and findings that were already established. Thereby, literature analysis was involved as a part of methodology to substantiate empirical models. After literature review, WLS

Multiple Regression analysis was selected as the first research method to investigate ICO crowdfunding stage. As a second research model that aims to explore how post-ICO market is affected by the two main cryptocurrencies with the highest market capitalizations, Vector autoregression technique was employed. First and second research models were developed by using software "R" and "Eviews" respectively.

Structure of the research. Thesis comprises of three main parts. The first part covers the background of blockchain-based token economy, market dynamics, analysis of ICO processes and diverse researchers' findings. In addition, this part involves the analysis of methods and variables used in related literature. Methodology part includes construction of two quantitative research models, variables, data collection and sampling principles as well as assumptions and their testing. Moreover, this part covers research limitations. The last part represents practical employment of twofold research as well as encompasses result analysis of ICO crowdfunding stage and post-ICO market performance analysis. Finally, conclusions and recommendations are introduced.

1 BLOCKCHAIN-BASED TOKEN ECONOMY: THEORETICAL BACKGROUND

Only since 2017, ICOs substantially gained popularity within blockchain community and became a global topic in recent academic analyses. As the interest in token offerings is newly arisen, the theoretical and empirical investigations lack the greater extent. However, the emergence of token sales raised a number of issues that the literature is beginning to undertake. Initial Coin Offerings are one of the recent “financialization” actors. “Financialization” addresses the trend of banking disintermediation, deregulation, increasing role of financial motives, agents and institutions that results the transformation in economies (Aalbers, 2016), as well as occurrence of finctech and blockchain-based technologies development (Lagoarde-Segot, 2017). In regards of ICO, the phenomenon promotes socio-economic changes – disintermediation and variation in ventures’ funding mechanism. Therefrom, researchers who analyzes aspects related with Initial Coin Offerings currently focuses on issues concerning legal interest and regulation (in regards of disintermediation), success factors, risks, opportunities and challenges caused by emerged phenomenon, value determinants in ICOs mechanism and post-ICO performance. The most important legal aspects related with ICO arises from the disintermediation and anonymity that ICO provides. Anonymity causes high uncertainty in cryptocurrency market and provokes fraudulent activities. Not to mention, ICO market contains many pros (no intermediaries, no geographical boundaries, easy and immediate funding for early stage ventures, etc.) as well as cons (asymmetry in information disclosure, speculative contributors, ect.), which are discussed more detailed in chapter 1.2.2 as well. The most widely analyzed topic in scientific literature is towards factors of success. Authors mostly focuses on agents related with communication signals, regulation, underpricing, and structure of project while analyzing the probability of ICO success (in accordance to Amsden et al. (2018) the criteria for successful ICO is met when project’s soft cap is reached).

1.1 The Fundamentals of ICO Mechanism

In general, Initial Coin Offerings are identified as an open and direct way for early funding promoted by organizations and entrepreneurs in order to increase financing through cryptocurrencies in exchange for originators’ issued “tokens”, that can be sold or used later on to obtain profits, products or services (Adhami et al., 2018; Fish et al., 2019; Chen, 2019). Moreover, all ICOs are executed by using blockchain technology and are initially launched to fund technology-based projects. Latter aspects are the main ones that differ ICO from Initial Public offering. The other important feature that emphasizes difference between ICO and other crowdfunding methods (crowdfunding, Initial Public Offerings, Venture Capital, Angel Investors) is that during the ICO investors do not buy the underlying asset, respectively, they buy the money supply of the future's project. If the project grows and the technology is well applicable, the value of tokens will positively correlate with the value of the company. However, in the beginning of the blockchain-based crowdfunding campaign denomination of tokens is equal to zero and originator's issued coins become more valuable when network of ICO project matures. In the initial stage, the value of tokens strongly depends on the users' perceived future's utility of the network. During the pre-sale stage, major investors are risk takers or those who firmly believes in the campaign. In the outset, early birds and their willingness to pay for the project give value for tokens. Over the time, more contribution is given to the ICO campaign and company begins to materialize, and become able to deliver for end users. The profit of different ICO projects vary greatly due to many aspects: technology, purpose of the project, usage of tokens, type of campaign, etc. Variety of token sales characteristics makes it difficult to compare and evaluate separate ICOs. For instance, from technical side, ICO can be executed using cryptocurrency blockchain, usually Ethereum technology, or project can be built on the unique blockchain (created specifically for the campaign) as well as it can vary from one technology to the other after the completeness of ICO. Likewise, associated usage of tokens differs between different ICOs, as well as project itself is diverse taking into consideration its aim, vision, mission, and future perspectives (Chanson et al., 2018a).

1.1.1 The Determination of Initial Coin Offerings Process

The blockchain and ICOs contains a sole form of banking disintermediation that is diverse from other concerned notions in the conventional financial industry (Chanson et al., 2018a). The process of ICO is complex and only cryptocurrency holders can be a part of ICO project (certainly, there are exceptions as, for instance, pre-sale stage). Before going further into movements of ICO, blockchain technology operating principles, limitations and advancements as well as cryptocurrency market should be discussed as it is essential to have a certain understanding of blockchain, knowledge of tokens/coins, and cryptocurrencies. Many aspects towards blockchain and cryptocurrencies are important to further analyze ICO market, as phenomena are interrelated. Aspects of cryptocurrencies that are valid for ICO analyses are as follows: variation of value, risks, exchange and trading possibilities, prevalence and market capitalization, legal regards, etc. While blockchain is important for its decentralization, technical advancements, and applicability opportunities. The process of ICO, decentralized token sales background and market dynamics are detailed discussed in subsequent sections.

Cryptocurrency market. The very first cryptocurrency Bitcoin was introduced in early 2009. Only in 2011 the price of cryptocurrency began to increase and in 2012 cryptocurrency started to gain a greater interest from investors, public as well as policymakers, economists, and even national governments. Cryptocurrencies simply can be defined as finite entries in an electronic database where no one is able to make any changes without the verification of the network participants. Primarily, open source coins were created to transmit funds without the intermediation (e.g. such as banks). Together with interest, cryptocurrencies brought to the attention legal, regulatory, as well as ethical challenges to the central authorities (Fry and Cheah, 2016). Latter issues mostly appears due to the user anonymity, which provides high speculation possibilities, promotes illegal activities, and expansion of Black market. For instance, some authors states that even ¼ of all Bitcoin users and about half of the BTC transactions are related to the illegal activities (Katsiampa, 2019).

In 2017 the value of Bitcoin skyrocket and in late 2017 reached the highest point where unit cost near € 19 000 (according to Coinbase.com). Corbet et al. (2018) proposes that this sharp increase in the price of Bitcoin is described to have bubble-like properties due to the speed of the increment. Currently, the price of Bitcoin increased to around € 12 000 (in May (2020), price was around € 5 000). Therefore, the fluctuations in cryptocurrency market are still significant and highly unpredictable in comparison to traditional currency (Brauneis and Mestel, 2018). Corbet et al. (2018) proposed the idea that Bitcoin is in a bubble stage since the price increased above € 1 000. Enlarged interest in Bitcoin has provoked an emergence of a numerous amount of other open-source digital coins based on decentralized technology (e.g. Ether, Zcash, Tether, Dash, Litecoin, Ripple, etc). There could be assumed that prices of cryptocurrencies are interdependent because that almost all digital currencies are based on Bitcoin but volatility dynamics in cryptocurrency markets are still left underexplored (Ciaian et al., 2018).

Blockchain Technology. Blockchain was introduced in 2008 as a virtual currency system that could change central authorities for issuing money units, making ownership trades, and confirming transactions. After occurrence of the Internet, decentralized technology is considered to be the most engaging invention. After its first establishment, blockchain has been improved over the time and now it is widely adopted beyond cryptocurrencies. For instance, Namecoin (decentralized name registration platform), Colored coins (allows developers to create new cryptocurrencies on the Bitcoin blockchain), also 900 DApps were implemented on the Ethereum platform, such as asset management, decentralized exchanges, etc. (Buterin, 2014; Lee, 2019). Blockchain-based platforms present decentralized decision-making processes in which the community around the platform not only proposes the changes to the code but also decides which of these changes should be realized through groups, voting systems, etc. (Akcora et al., 2017). In general, blockchain consists of P2P networks, public and private key cryptography, and distributed mathematical algorithms. All recorded information is deployed in blocks that are chronologically added into the chain (Nair & Sebastian, 2017).

To ensure transparency, reliability and reduce possibility of falsification, every block in the chain cares not only information about the actions made through the system, but also a unique hash and includes a hash from a previous block. Once hash is changed, it is no longer the same block in the system. Furthermore, when action in block is completed, blockchain increases and a copy of the system is automatically sent to nodes of the network meaning that the block cannot be modified (Lee, 2019). Blockchain-based platforms provide decentralized systems for verification processes and transactions. Immediate platforms do not require third party interaction, consensus is ensured between users through the state of the ledger and cryptography, which involves validators in the process (Davidson et al., 2018a). In addition, decentralized technology includes smart contracts, which are self-executing agreements that enable automated actions in the platform. As an example, financial derivative is one of the most common application of smart contracts (Buterin, 2014; Davidson et al., 2016).

Bitcoin blockchain has some limitations that interfere the broad usage of the technology. For example, one of the main is incomplete Turing language or "blockchain blindiness" (that excludes feasibly valuable source of randomness) (Buterin, 2014). The wide adoption of the Blockchin came up with the establishment of Etherium technology. Vitalik Buterin (2014), the founder of Etherium, improved the concepts of scripting, meta-protocols, and gave the ability to programmers to create consensus-based platforms with feature-completeness and facilitated development. In accordance to the author, Etherium is capable to incorporate these features due to Turing-complete programming language, which allows anyone to introduce smart contracts and launch decentralized platforms with their own rules and functions. As a result, more advanced technologies are expected to be introduced over the time, e.g., saving wallets, crop insurance, decentralized data feed, and many others (Buterin, 2014). Thereby, blockchain has the potential to establish new substructures for both economic and social systems (Iansiti & Lakhani, 2017). For instance, Decentralized Autonomous Organization (DAO) was established to replace crowdfunding because it allows transparent revenue distribution to participants (unfortunately, the project failed due to external hacking) (Lee, 2019).

However, the DAO project attempted a new approach to early financing: the use of tokens in the decentralized network is not only a new manner to financing but also a new method of creating a venture's own networking (Lee, 2019; Chen, 2018). It will take a lot of time to adopt the technology to replace existing infrastructures – it is a progressive and constant process. Therefore, Initial coin offering is considered as a new method of funding for early stage companies as alternative to conventional sources (VC, angel investors, crowdfunding, etc.).

Initial Coin Offerings. Before the creation of ICO campaign, financing seeking company produces two smart contracts that are deployed on the blockchain platform to determine key parameters of token sale project. Even 90 % of ICO in the market are based on Ethereum blochchain, nevertheless, when initiating decentralized crowdfunding, company can build its own blockchain. When originators decide to do so, potential contributors are sold a Simple Agreement for Future Tokens (SAFT) as a guarantee of property of the tokens once the new technology is complete (Amsden & Schweizer, 2019). Notwithstanding, to create own blockchain for ICO is expensive and very difficult from technical perspective. Amsden & Schweizer (2019) also indicates that implementation of own decentralized technology would require the company to establish an ongoing incentive mechanism to attract users in order to verify the ledger. Smart contract that is located on the blockchain defines the hard and soft caps, quantity of the tokens, period of the project, etc. Also, additional smart contract is created for token distribution and transfers that can be executed after the launch of the project. Moreover, funding is not transferred directly. After the payment, the subsequent process is fully automated by the pre-defined rules in the smart contracts: ICO campaign automatically receives the access to the funding from ICO Smart Contract (Figure 1:1) and investors automatically get their portion of issued tokens from the Token Smart Contract (Figure 1:2). (Chanson et al., 2018b).

Stages of ICO. In general, literature identifies three stages of ICO: pre-ICO, the main stage, and post-ICO (shown in Figure 1: pre-sale, disclosure of token sales, and post-ICO stage). At the pre-ICO stage originators of the ICO project discloses white paper to provide the information for potential investors about key aspects of the project. White paper contains information such as prime idea, technical details, members of the company that initiates the ICO, the number of tokens and their target prices (Zetzsche et al., 2018). White papers do not have any guidelines or standards how to be filled and disclosed, therefore one electronic documents are more detailed than others, which, in accordance to Fish (2019), causes information asymmetry in ICO market. Besides, some entrepreneurs announce the advisory board in order to show the quality of the campaign, and employs experts (for instance, from legal, marketing, or information technology departments) to run the ICO (Chen, 2019).

Furthermore, in the pre-ICO stage pre-sales are initiated in order to examine the market readiness and acceptance level. Pre-sales increase the interest in ICO thus attracting greater attention from the public and enhancing the willingness to invest in particular ICO (Masiak, 2019).

Adhami et al. (2018) agrees that pre-sales are one of the major factors that fosters the higher probability of ICO project success. At the pre-sales, investors are able to use fiat currency that helps to simplify the process for non-users of cryptocurrencies and accelerates the accumulation of soft cap (Masiak, 2019). However, Domingo et al. (2020) argues that pre-sales are related to ICO success but it negatively affects project's returns. During the main stage, company seeks to collect predetermined hard cap and exchange issued tokens for cryptocurrencies. At the post-ICO stage, originators of token sales exchanges cryptocurrencies to fiat money to reach their goals of the project: make an investment to develop the product, further expand business, etc.

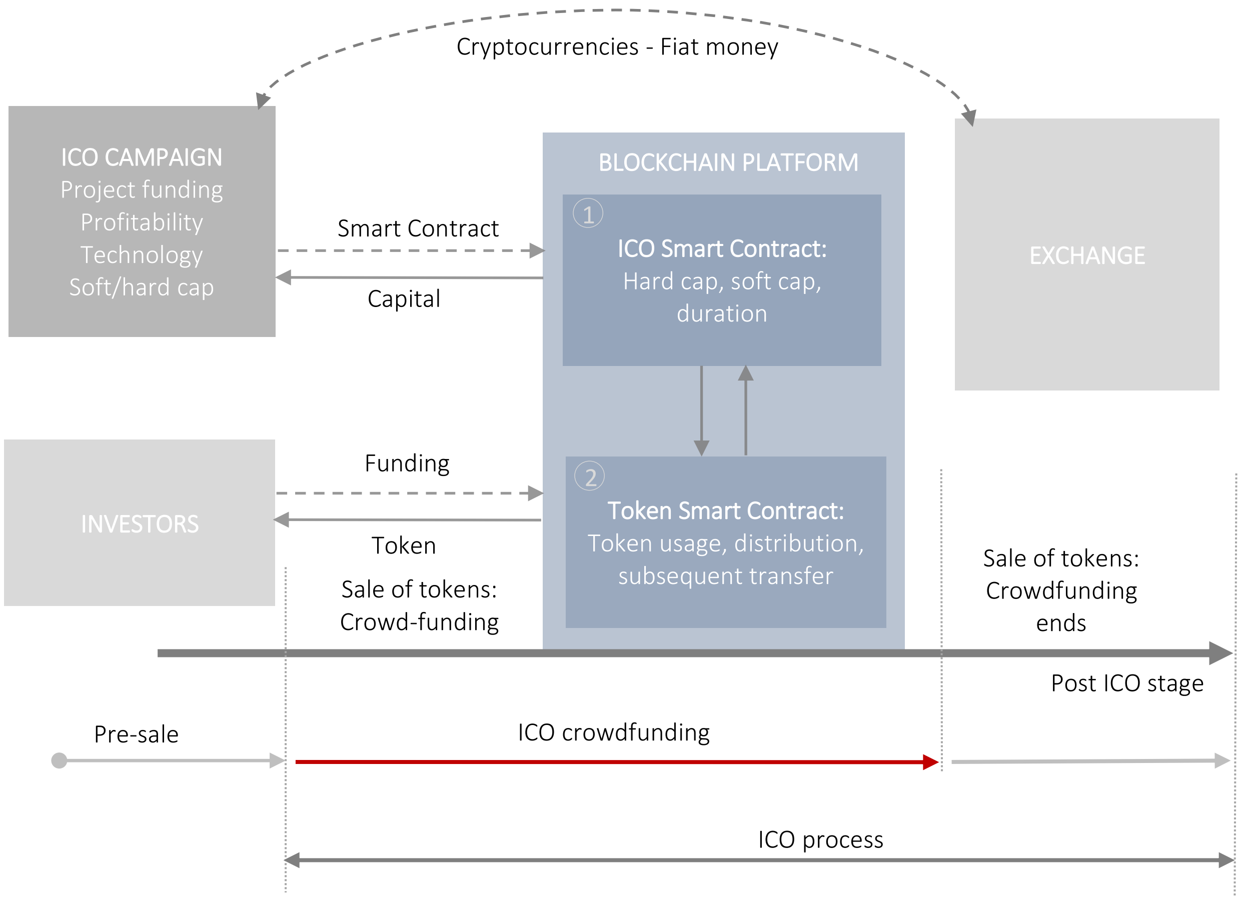

Figure 1. Initial Coin Offering: process and stages (without listing stage)

Source: Compiled by an author according to Chen, 2019; Masiak et al., 2019, Chanson et al. 2018

Additionally, some ICO companies give the opportunity to trade their tokens on a secondary market (indicated in Figure 2: disclosure for listing). This latter opportunity is comparable with an IPO, but tokens/coin are traded only on cryptocurrency exchanges (Chen, 2019; Masiak et al., 2019). According to the authors, during the listing, the main factors that influences token price are company's disclosures on social media, code updates, and token sale performance in in the main stage. Moreover, Chen's research (2019) ascertains that the value of listed tokens is very sensitive to low credibility and easy-interpretable signals. Investors considers listing of tokens as a positive factor and ICOs with planned secondary market trading possibility tend to collect more capital. In addition, the liquidity in token market is considerably high. However, to seek for admission to trading, firm must be listed on the exchange (the preparation for listing takes time; around several months). Further, as trading exchanges provide the ability to exchange tokens to fiat money or cryptocurrencies, some investors seeks to use this opportunity if the price of the token increases.

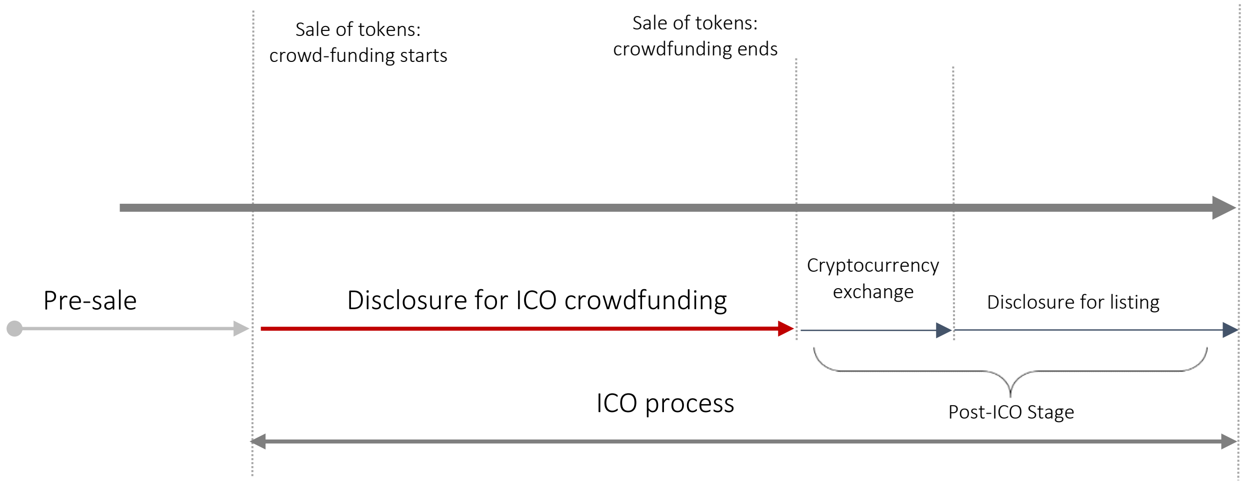

Figure 2. The stages of Initial Coin Offering including listing stage

Source: Compiled by an author in accordance to the Chen, 2019, Chanson et al. 2018

Nevertheless, not all ICO projects have the listing stage, it depends on company's resources, purposes, and capabilities to improve project. The structure of ICO is in the great variety and mostly depends on the objectives of the project as well as the abilities to expand business, campaign success and profitability.

1.1.2 The Comparison of ICO and Other Funding Methods

Nowadays, there are many ways to collect initial funding. For instance, crowdfunding, venture capitals, angel investors, Initial Public offerings are the main ones. All methods differ and mostly are used for different purposes. Each way of funding requires diverse capabilities and structure of the fund collecting company. Therefore, the occurrence of ICO brought a new form of entrepreneurial finance that shares some qualities with conventional financing methods but also adds some more opportunities.

Crowdfunding is the collection of small amounts of money from a huge number of individuals. It is a long process, which requires considerable dedication. In accordance to Fisch (2019), ICOs and crowdfunding has similarities as in both ways company seeks financing from a broad network investors and usually non-professionals. In this way of funding investors, pool their money together in small individual contributions in order to support a specific goal (Block et al., 2020). In addition, both ways of financing gives low protection to investors and provides limited available information and no supervision (Domingo et al., 2020). In comparison, angel investors are entrepreneurs that gives funding in exchange for companies shares. The process is shorter, angel investors could give advices and good guidance, but later on, they could demand for some control in the firm. Moreover, angle investors could provide help with company's management and offer expertise. A third type of funding is venture capitalists. They could give a large amount of money in engage for firms shares (as well as angel investors), but they invest only if company has a guaranteed good potential. Table 1 provides comparison of diverse funding approaches.

Table 1

Differences Between other funding methods and ICOs

QUALITY / METHOD	Secondary market	Early investment	Broad investors' network	Control demand	Supervision	Small amounts	Large amounts
ICO	×	×	×			×	
Crowdfunding		×	×			×	
Angel Investors		×		×	×		×
Venture Capitalists				×			×

Source: Compiled by an author in accordance to Chen, 2019; Momtaz, 2020; Block et al., 2020

ICO is mostly compared with IPO (Table 2) because processes of funding have similar features such as possibility to trade issued instruments in a secondary market (Chen, 2019). Nevertheless, there are many essential differences between ICOs and IPOs, which attracts diverse types of investors (e.g. investors of IPO should have lower risk tolerance apetite than ICO investors). In IPO process, issuer provides stocks to investors, and in general, those stocks provide voting power in the company and dividends. In ICO process, originators of the project provides investors with a variety of rights, depending on the type of ICO (discussed in section 1.1.1). In addition, IPO investors requires public accountants, auditors, lawyers and banks, which make the process of funding longer; in ICO only programmers are required (Felix et al., 2019). As a result, ICO do not need to take even a month in order to settle funding. In addition, ICO is mostly designed for start-up companies, so to initiate a project track record is not required. On the contrary, IPO must provide an adequate track record of historical company's performance (Felix, 2019).

Unregulated environment and lack of participation of parties with good public reputation, ICO contributors may be deluded by fraudulent projects, because only a few participants may know exact real features of initiated token sale (Zetzsche et al., 2017, Chod and Lyandres, 2018).

Table 2

Differences between IPOs and ICOs

IPOs	ICOs	Explanation
Long process (4-5 months)	Quick process (1 months)	As IPO market is heavy regulated, IPOs take more time to set-up than ICOs
Defined rights; clear information disclosure	High information asymmetries in the market	ICO gives a great variety of but exposure is narrowed to a specific projects; IPO rights apply to the overall success of a company
Mostly institutional and private investors	Weak network of primary investors	IPOs has a strong community of mostly professional investors; ICOs investors are mainly crypto investors
Strictly defined reporting and disclosure requirements	No requirements for reporting and information disclosure	Lack of transparency in ICO market
Fraud is rare within IPO market	Considerably high possibility of fraud	Equity financing requires companies to show valuable history; ICO market is absent of regulations that may result in fraud

Source: Compiled by an author in accordance to Amsden et al., 2018; Felix et al., 2019

Overall, ICO market is riskier than IPO and investors are more risk seeking (Lee et al., 2018). However, according to Fisch (2019) if ICO campaign is well designed, ICOs could even grant more security, liquidity, and transparency than traditional financing ways. Therefore, ICO brings challenges to conventional funding approaches but also imparts new opportunities to organizations. Startups can issue tokens and create unique structure that is self-governed via smart contracts and economic inducement generated by the underlying token.

1.2 The Overview of Blockchain-Based Token Market Dynamics

The significance of investors' motives to invest in ICOs is open to differing interpretations and understanding investor incentives is a difficult assignment. Thus, there is a growing body of literature trying to investigate the causes. Additionally, the primary difference between investors' profiles are their aim of investment, which can impart value via utility or security function. Utility tokens are used to obtain product/service in the future or can be used as a medium of exchange on the cryptocurrency markets. In opposite, security tokens entitle holders to shares of the ownership. However, some authors provided that not only investor profiles but also disclosure signals influences investment decisions. Therefore, this section provides analysis of different types of token sales, motives of ICO participants and challenges as well as opportunities brought by ICO.

1.2.1 Motives of ICO Investors, Information Signals and Disclosure

There are many types of ICO campaigns, which also attract different types of investors. The main differences are the idea, the structure of the project and type of tokens. The very first token sale was referred to as Initial Coin Offering, but since the phenomenon has evolved, companies started to issue other types of sales (indicated in Table 3).The most prevalent are three sorts of tokens: currency, equity, and utility (Masiak et al., 2019, Fisch, 2019).

Table 3

Types of Tokens in ICO

TYPES	DESCRIPTION
Currency tokens	Used as medium of exchange to buy goods/services or can be used as a means of money.
Utility tokens	Provide investors with an access to a product/service that is created by the ICO campaign (e.g. EndChain).
Equity tokens	Presents the asset of the ICO campaign, such as a debt or equity (e.g. DAO)
Hybrid tokens	Tokens that could be both securities and medium of exchange.
Pre-sale tokens	Investors receive tokens, which entitle them to acquire other different tokens at a later date (similar to rights issues).

Source: Compiled by an author in accordance with Swiss Financial Markets Supervisory Authority (FINMA), 2017; Fisch, 2019; Masiak et al., 2019; Momtaz 2020

The issue of different type of tokens increases the attractiveness of ICO project and is one of the main distinctive substantial feature between different token sales campaigns. However, Adhami et al. (2018) complains that marketing and usage of tokens only slightly influences prosperous in ICO mechanism, especially comparing with presale's impact on ICO success.

Furthermore, Fisch et al. (2019) analyzed causes and profiles of ICO investors. Author emphasized that investors are motivated by diverse set of intrinsic and extrinsic motives, yet more driven by intrinsic causes, since ICOs are not very popular between professional investors. The main intrinsic causes that drives individuals to invest in ICOS are anonymity and decentralization, while extrinsic incentives are return and interest of secondary market trading reason. By incorporating factor and regression analyses, author investigated relations between technological, sociodemographic, ideological, and financial motives. Researcher identified that technological motives are ones of the most important to ICO investors compared to other causes due to confident in blockchain technology and its potentials. However, Chen's (2019) study suggests that investors' decision might be affected not only by the motives but also by the data provided through different channels. Each investor may understand and interpret information differently due to the diverse disclosure channels. One of the main channels are open source codes repository websites, where aspects of ICOs technology are reflected in its open-source codes rather than patents (Fisch et al., 2019). Other main channel is "white papers", official venture's disclosures on social media and the Web that is easily accessible to investors in general. Schückes and Gutmann, (2020) disclosed that ICO contributors are interested in blockchain-based token sales because it does not require heavy resources input and gives considerable funding outcomes in a cryptocurrency market. In addition, it provides value added services through the investor network. In addition, Chen (2019) indicated a concern regarding asymmetric information related with regulation of ICOs. In the environment where regulation is low, the credibility of communication channels is crucial aspect for investors. For instance, a "white paper" may be effective signal in contrary to patents. Both "white paper" and patent provides characteristics of venture's technological aspects, but "white paper" is less legally restricted (Fish, 2019). Patents have a requirement that ICO event cannot be exposed before disclosure of patent, while "white papers" can be published even when the code is revealed. Therefrom, "white paper" could be used as a substitute for ICO patents. Likewise, it may be that ventures with low technological capabilities try to hide its capacity by providing details in nontechnical way while using "white paper" (Fisch, 2019). Moreover, by analyzing relation between total money raised in crowd sale (from 2015 to 2018), underpricing and signals from official announcements, open source code, social media, author emphasized that high information asymmetry in ICOs exists. Findings of the research suggested that companies should disclose information in “white papers” for common investors as well as create open-source code to experienced investors in order to increase credibility and ensure fairness. Momtaz (2020a) indicated that ICO markets are inefficient because investors are largely unable to identify spurious information delivered by ICO campaigns. According to the author, inefficiencies transpire only gradually and after ICO is initiated. Fisch (2019) suggests that there are two criteria, which impose the effective ways of reducing information asymmetry: the information should be noticeable and costly (e.g. not only monetary, it might be time, efforts to find information, etc.). In accordance to Connelly et al. (2011), if signal do not include costs, it can became easily counterfeiting and information loses its value as well as trust.

Further, Masiak et al. (2019) indicated that cycles in ICO market exist as well as shocks to the growth rates of ICO volumes. In accordance to the author, shocks in cryptocurrency returns have a substantive and affirmative effect on ICO extent. However, cryptocurrency returns do not significantly influence ICO volumes but innovations in Bitcoin or Ethereum are found to have significant influence to ICOs in up to eight weeks after the impact occurred. Additionally, bullish/bearish market in ICOs persist for around 4 weeks (Masiak et al. 2019).

1.2.2 Opportunities and Hazards Brought by ICO Phenomenon Occurrence (SWOT)

The prevalence of Initial Coin Offerings around the world brings many benefits to the business but likewise imparts plenty challenges and risks for market authorities, enterprises, investors, etc. (identified in SWOT analysis Table 4). ICO participants can easily avoid regulation rules and costs that are applied to businesses issuing their securities to investors in exchange markets (Masiak et al., 2019). However, ICOs are controversial; ventures implementing token sale campaigns might collect huge amounts of money without any insurance to contributors, investors and by providing limited data (Fisch et al., 2019). Equally important is that tokens in ICO mechanism do not have current value, no pricing mechanism is applied and projects are very speculative, giving a high potential for fraud (Chen, 2019). Therefore, only few business ideas in ICO market realizes. As companies initiating IPO already have the actual product, usually ICO companies have only the idea of the product or service, thus it is difficult to assess the profitability of the project and the time frame when project will start to give profitable results (Amsden et al., 2018, Chen, 2019, Masiak, 2019). In the same way, high information asymmetry heavily occurs in ICO market (Chen, 2019). As a result, ICO market lacks of transparency. Nevertheless, there are many reasons of why accepting innovative technologies are important to the business. Adhami et al. (2018), Fisch et al. (2019), Amsden et al. (2018), emphasized main causes: by adopting DTL, business could reduce costs of fund raising; avoid intermediaries; token mechanisms allow building a post-ICO market for their investments with high liquidity; avoid geographical boundaries, have the access to open source for capital, etc. Not only latter facts but authors also indicate that ICOs are less expensive, include fewer parties, and are easier method to collect funding in comparison to angel investors or venture capitals.

Table 4

SWOT analysis of Initial Coin Offerings

STRENGTHS	WEAKNESSES
Participants of ICOs provide direct and rapid funding for ventures.	No pricing mechanism specified for token sales.
Lower costs due to intermediaries and absence payment.	Information asymmetry exists between external investors and entrepreneurs and is especially heavy in the cryptocurrency market.
ICOs are open – no strict time for investment; availability for early contribution agents.	Lack of transparency in the ICO market due to the absence of mandatory disclosures.
OPPORTUNITIES	**THREATS**
Tokens can be traded on the secondary market – high liquidity.	Lack of regulations increases investment risk.
Blockchain provides possibility for secure transactions.	The sensitivity to regulations can lead to the depreciation of tokens (or even bankruptcy).
ICOs gives opportunity to test marketability and provides flexibility and mobility for the project.	Hackers possess a major risk to ICO.
Lower competition – allow a potentially easier way to collect funding.	Lack of value determination leads to a highly speculative market and high potentials for fraud.

Source: Compiled by an author in accordance to Adhami, 2018; Fisch et al., 2019; Chen, 2019; Huang, 2019; Masiak et al., 2019; Domingo et al., 2020

Additionally, ICOs involve nonprofessional investors by providing easier way of participation in startup financing, hence increasing greater liquidity and reducing monitoring costs (Masiak et al., 2019). On the other hand, those investors may just follow other contributors without taking into consideration and assessment any other facts without their own experience. This may lead to irrational herding behavior in ICO markets (Masiak et al., 2019). Investors of ICOs provide the company with early-stage funding that is available to the venture directly and immediately. Also, tokens can be traded on a post-ICO market to raise funds, and the liquidity is considerably high (Fisch et al., 2019). Moreover, as there is absence of regulations in ICO market. No restrictions are applied to investment and marketing (Amsden et al., 2018), which leads to the easier and faster preparation to collect funds. Although this may be true, but no regulations are applied for information that should be disclosed and even more injurious is the fact that no one supervises the information that is disclosed. This may lead to counterfeiting of the project in order to collect more money.

Initial Coin Offerings have introduced society important advantages, such as anonymity, security, and capitalization. The anonymity and disintermediation are the main aspects that has brought ICOs to the horizon of policy makers. As an example, the Financial Conduct Authority in the UK forewarn that ICOs highly fraudulent, while China recognized ICOs as undesirable illegal financing behavior. ICOs can be identified by ventures as a rapid and operative way to rise capital without compliance pressures from regulators. As an outcome, many firms are able to rise funding exceeding their actual needs in the short term. (Zhang, 2019). In order to avoid fraudulent activities, governments started to implement different approaches to deal with both cryptocurrencies and occurrences involving them (An et al., 2018). For instance, in 2017 Switzerland adjusted its legislation in order to support fintech activity in the country. The Swiss Financial Market Supervisory Authority (FINMA) stated that there are no specific regulations for ICO. However, there are still diverse possibilities to cover ICOs (Kaal, 2018). Switzerland financial market law complies with the technology neutrality: market is not regulated in general under supervisory law if there is no obligation for repayment, if no secondary trading is included and payment instruments issued (FINMA, 2017). Chinese government prohibited the entire cryptocurrency market including ICOs as well. As a fact, prohibition caused vast price fluctuations in both cryptocurrencies Bitcoin and Ethereum. According to Fixh and Momtaz (2020) research findings, market without intermediation can be inefficient. Therefore, intermediaries (institutional investors) might earn substantial financial gains from eliminating those market inefficiencies. However, Canada has very positive provision in regards to cryptocurrencies and ICOs. Country is seeking to explore potential of blockchain and the phenomenon related to it. Canadian Government carefully assess ICOs and which regulations should be implemented to grant the approvals to ICO (Zhang, 2019). Therefore, Canada promotes investments in innovations related with blockchain technology. However, according to Domingo et al. (2020), the sensitivity of ICOs to implied regulations can lead to the depreciation of tokens and even bankruptcy of campaign.

Moreover, ICO projects are more prevailed in one countries relative to others, as well as success factors of ICO differ among countries. Many agents influence the pervasion of token sales, and yet aspects are not widely discussed in existing researches. However, An et al. (2017) investigated that countries with stronger legal institutions and investor protection tend to have a more developed ICO markets. Huang et al. (2019) pointed out that developed financial markets are crucial determinant for ICOs and successful token sale campaign, as it allows creating innovative digital services, leads to the productivity improvement, and fosters the economic growth.

Another important aspect is regulation. There could be assumed that regulation for cryptocurrencies and ICOs is high, the prevalence of token sales is low. Notwithstanding, based on Huang's et al. (2019) research, countries that introduces intentions on regulation of ICOs pulls more token sale projects than those states, which intends banning or takes no actions. Therefore, ICOs are more attracted by the clear regulation framework than by no restrictions at all. ICOs where investors have voting rights and higher quality of information disclosure tend to raise more funds. Therefrom, the importance of investor protection is valid in the development of ICOs market (An et al., 2018). Consequently, ICOs takes place more in those countries where equity crowdfunding is highly developed. Looking into 2017 data, the year when ICO incidence significantly increased, the top seven countries with the highest number of ICOs were as follows: United States of America (178), Russia (111), United Kingdom (80), Singapore (75), Switzerland (46), Canada (29), and Estonia (29). Literature emphasizes that financial innovations are more plausible to appear in states that has more secure internet servers and advanced digital technologies (Haddad et al., 2018). Notwithstanding, Huang et al. (2019) argues that explicated digital technologies are not enough for token sale prevalence; country needs to have well developed investment-based crowdfunding platforms. Regardless the attempts implementing regulation in cryptocurrency and ICOs markets by auditing various cryptocurrency exchanges, introducing tax reports and legal guidelines, token market and ICO processes in general persist unregulated (Chanson et al., 2018). Nevertheless, as ICOs track time-related sequence, the qualities vary substantially. Therefore, regulations are difficult to implement. The process requires standardization, clear explanation and justification as well as enforcement of fairness standards (An et al., 2018). The efforts to implement regulation on cryptocurrency and ICO market caused equivocal situations because of broad variety and different structures of ICOs (Zetzsche et al., 2018), as well as cause conflicts of law (Barsan, 2017) because of geographic distribution of ICO contributors blockchain-based token sales have no territorial boundaries.

ICO has become a reliable way for fundraising and even though ICOs have been successful, they come with some disadvantages as well. The lack of regulations is one of the main risks caused by ICOs. Therefore, governments and policy makers try to find some ways of regulating ICOs (especially active movements were observed in 2019). However, as already discussed, regulations are difficult to implement in cryptocurrency markets.

1.3 The Summary of Literature Regarding Blockchain-Based Token Economy

During the past 3 years, ICO has emerged as prosperous way to collect funds and became an alternative for traditional funding strategies. As identified in previous sections, ICOs have brought many benefits to society but likewise introduced many challenges, which academic literature is starting to undertake. An amount of empirical researches towards ICO economy is rapidly evolving and authors has already prepared various important insights. The researchers mostly analyzed aspects relating determinants of success and value, legal aspects, information disclosure, comparison between diverse funding methods and ICO, hazards and opportunities, ICO returns. However, there is still lack of scientific researches regarding post-ICO market performance.

In order to produce comprehensive analysis of the research, suitable methodology must be prepared and expedient variables selected. Therefore, scientific literature is analyzed not only by collecting relevant insights regarding the topic, but also by outlining methods and predictors used for particular problem. As a result, this chapter begins by introducing main problems analyzed in scientific researches. The subsequent sections provides the summary of methods and variables used in literature towards ICOs.

1.3.1 Scientific Problems Analyzed in Academic Literature

This section provides an overview of the main problems that occurred in recent literature and results of already completed researches.. As can be seen from compendium (Table 5), Fish et al. (2019) and Masiak (2019) analyzed motives of ICO investors. They pointed out that motives can be break down into 3 categories: ideological, technological, and financial. In addition, the result of analysis shows that ICO contributors are mostly driven by the technological motives because they have interest and sees high potential in the blockchain-based projects. Chen (2019) and Fisch (2019) analyzed the asymmetry in ICO market. White papers do not have any guidelines, standards, or agreed regulation how to be filled and disclosed. As a result, some electronic documents are more detailed than others are and can be interpret differently by every individual. The latter issue, in accordance to the authors, causes information asymmetry in ICO market.

Table 5

Summary of issues analyzed in regards of ICO and results of researchers

SCIENTIFIC PROBLEM	RESULTS	YEAR	AUTHOR
What factors affect ICO returns?	(1) ICOs are highly volatile and are high-risk investment. (2) An increase in Bitcoin returns leads to the increase in ICO returns. (3) Pre-sales are related to ICO success but it negatively affects returns.	2020	R.S. Domingo; J. Piñeiro-Chousa; M.A. López-Cabarcos,
What is successful ICO? How it affects ICO markets?	(1) The most valued tokens are utility that gives access to future products and services; significantly contributes to ICO success; (2) Successful ICO increases levels of future employment.	2020	S.T Howell; M. Niessner; D. Yermack
What are main motives that drives individuals to invest in ICOs?	(1) Motives are break down into ideological, technological, and financial categories. (2) Technological motives are the most important to ICO investors compared to financial motives and ideological motives as contributors are confident in blockchain technology and its potentials.	2019	C. Fisch; C. Masiak; S. Vismara; J.H. Block;
What are market cycles of Initial Coin Offerings (ICOs) and their relationships with Bitcoin and Ether?	(1) Shocks in cryptocurrency market have a significant and positive effect on ICO volumes. (2) The volatility in cryptocurrency market does not affect ICO incidence. (3) Innovations in cryptocurrency market affects ICOs affirmatively.	2019	C. Masiak; J.H. Block; T. Masiak; M. Neuenkirch; K.N. Pielen;
Why ICOs are popular in some countries and not in others?	(1) ICOs occur more often in countries with well-developed financial and equity crowdfunding markets, clear regulatory framework for ICOs	2019	W. Huang; M. Meoli; S. Vismara;
What leads ICOs to be successful?	(1) Venture uncertainty is negatively related, while higher venture quality is positively related to ICO success. (2) Higher price of Ether (decreasing the relative attractiveness of ICOs) is negatively related with ICO success. (3) Information about hard cap and high quality of code increases volume of investments in ICO.	2018	R. Amsden; D. Schweizer; C. Fish;
How ICOs allows entrepreneurs to generate buyer competition for the token, giving it value?	(1) Venture returns do not correlate with growth in the supply of tokens, but initial funds. (2) To collect funds in ICO is more limited than in IPO because the value of the tokens depends on a single period of demand.	2018	C. Catalini; J.S. Gans.

Source: Compiled by an author

Moreover, W. Huang, M. Meoli, S. Vismara (2019) analyzed legal and regulatory aspects of ICOs. The main concern of the research is why in one countries token sales are more prevailed than in other. As a result, ICO initiators are more interested in countries which have well-developed financial markets as well as clear legal and regulatory framework for token sales. In addition, Haddad et al. (2018) underlines that those financial innovations more often appear in countries that has greater number of secure internet servers and digital technologies. As a contrary, Huang et al. (2019) argues that advanced technologies are not enough for ICO spread, well developed investment-based crowdfunding platforms are also crucial. An et al. (2017) complements that countries with investor protection has more developed ICOs. Chanson et al. (2018a) and Barsan (2017) has emphasized that implementation of regulation in ICO market could cause law conflicts due to absent of geographical boundaries.

The most broadly analyzed topic towards success factors of ICOs where analyzed by Chen, 2019; Fish, 2019; Adhami et al., 2018, Amsden et al., 2018; Felix et al., 2019; Chanson et al., 2018. Authors argued that success is not affected by the availability of white paper but rather by the set of open source codes introduced for the ICO project. Fisch (2019) generally agrees that increased amount of funding is highly related with the quality of code. In addition, researcher indicates that success in ICO is associated with credible commitment to the ICO as well as quality information disclosure signals. Furthermore, Adhami et al. (2018) showed in his analysis that success probability increases when campaign collects earlier funding as well as it depends on the structure of an ICO.

In year 2020, the most analyzed topic is in regards to ICO market returns and ICO market efficiency and information asymmetry. For example, Fisch and Momtaz (2020) analyzed the role of institutional investors. They have indicated that intermediaries (such as institutional investors) can overcome market inefficiencies through superior screening of the information and coaching capabilities. Domingo et al. (2020) investigated influence of the ICO pre-sale, structure of ICO, Bitcoin returns (spot and future) on ICO returns. Authors justified that Bitcoin returns have a positive influence on ICO returns while pre-sales and ICO structure has negative influence.

1.3.2 The Analysis of Methods Applied in Academic Researches

In order to select the most applicable and plausible methodology for the analysis of blockchain-based token economy, similar researches have been examined. Therefore, this chapter imparts an overview of the main methods and most common variables that were used in recent literature.

Methods. Among academic researches, the most used method was Multiple Regression analysis. Authors that have applied regression analysis mostly examined the success factors, geographical distribution of ICO, underpricing and legal aspects (e.g. Chen, 2019; Huang et al., 2019, Amsden et al., 2019, etc.). In addition, some authors used different models to analyze success of token sales, e.g. Adhami et al., 2018 exercised monovariate statistical analysis, where Fisch et al. (2019) used instrumental variables analysis and measured two dimensions of operational progress. Masiak et al. (2019) examined shocks and relationships between cryptocurrencies and token sales by using vector autoregression (VAR), Granger causality tests and robustness tests. Most used methodologies are indicated Table 6. Moreover, many other specific analysis methods were used in recent studies as well. For instance, combination of formulas reflexing the upfront cost of initiating ICO (Catalini et al., 2018); empirical study and Beta survey for general overview of ICO market (Chanson et al., 2018); etc.), but they are not included in further analysis due to the different objectives and design of the research modeling.

Further, Fisch (2019) in his analysis towards success factors for raising capital used multivariate analysis. The OLS regression analysis was established with “amount raised (log.)” as the dependent variable. Researcher applied a Breusch-Pagan test, which indicated that the error terms might be affected by heteroscedasticity. As a result, all models in this analysis were estimated with heteroscedasticity robust standard errors. For more deep analysis, researcher used alternative estimation techniques and additional control variables: Shapiro-Wilk test for normality testing to indicate if the residuals deviate from a normal distribution, and generalization of linear regression that permits to use dependent variables, which have other error distribution than normal. Amsden et al. (2018) for decentralized blockchain-based token sale success analysis used three models for each separate dependent variable (because ICO success in this analysis is measured by three factors: total fund raised, trading, and CMC trading). Two logistic regression models were applied to analyze the factors of whether the tokens are traded (dependent variable - binary). To analyze aspects of the amount raised in the ICO, the OLS regression model were used. In all three models, variance inflation factors (VIFs) were used to check the multicollinearity given that the maximum VIFs are below the threshold of 5 (VIFs in the analysis showed no multicollinearity). Chen (2019) also employed regression analysis while investigating how signals from different channels might be used for token pricing. Researcher made two models: (1) to test correlation between dependent variable and predictors in pre-stage of ICO mechanism; (2) to test the same dependencies in listing-stage ICO project (more about ICO mechanism stages in chapter 1.1.1). Huang et al. (2019) examined the geographical distributions of ICOs. For the analysis, authors used negative binomial regressions on the number of ICOs by country. In this research, 6 different models were developed to test 6 separate hypotheses. Authors used robustness test to check the reliability of the models for each hypothesis. The latter test shows how results of the model change when the assumptions are change. For instance, in regards of taxation, different models for robustness test were made: (1) based on tax burden, while (2) based on tax havens, etc.

Table 6

Methods used in researches that analyses ICO related aspects

METHODS / AUTHORS	Binomial Regression	Regression analysis	Factor analysis	Monovariate statistical analysis	Vector autoregression (VAR)
C. Fisch; C. Masiak; S. Vismara; J.H. Block (2019)		×	×		
C. Masiak; J.H. Block; T. Masiak; M. Neuenkirch; K.N. Pielen (2019)					×
M. Chansom; J. Gjoen; M.Risius; F. Wortmann;		×			
W. Huang; M. Meoli; S. Vismara (2019)	×				
K. Chen (2019)		×			
R. Amsden; D. Schweizer (2018)		×			
S.Adhami; G. Giudici; S. Martinazzi (2018)				×	
J.An; W.Hou; X.Liu (2019)		×			
P.P. Momtaz (2020a)		×			
T.H. Felix; H. von Eije (2018)		×			

Source: Compiled by an author

Masiak et al. (2019) investigated market cycles and relationship with Bitcoin and Ether. First, researchers used vector autoregression model to three time series. Authors applied two recursive schemes to find the effects of shocks on the ICO growth rate, on Bitcoin returns, and on Ether returns for all the variables in the model. Research model faced a correlation of the error terms across equations (e.g. the effect of movements in bitcoin on ICOs, as typically the other variable (i.e., ether) co-moves with the changes in bitcoin). Therefore, reduced-form VAR transformation was required into structural in order to identify clear shocks. For model transformation, a recursive identification was used that orthogonalizes the residuals, which are completely uncorrelated. In addition, the Granger causality test was performed to validate variables of the model.

ICO underpricing studies (Felix et al., 2018) use Multiple Regression analysis as well to predict dependencies between underpricing (outcome variable that is calculated by $(P_i - E_i)/E_i$, where P_i is the close price and E_i the offer price of ICO. For normal distribution checking on the level of underpricing, researches employed Jarque–Bera test. The result of the test rejected the null hypothesis, therefore, authors added non-parametric Wilcoxon signed-rank test to T-test. Also, for heteroscedasticity verification, white heteroscedasticity and a Breusch–Pagan tests were applied. Employed tests have not rejected the null hypothesis for homoscedasticity, however, authors still used robust standard errors. As an argument, to use heteroscedastic data become common practice in empirical finance researches. Moreover, authors used VIF verification for multicollinearity testing (threshold used: 10). Moreover, analysis also includes Cooks Distance approach to identify outliers.

Variables. The features of ICO also have impact on successfully reaching ICO minimum funding goal. Different types of tokens (discussed in section 1.2) define the main distinctive features between various ICOs projects. The type and features of tokens could increase the attractiveness for investors thus implementing successful ICO campaign. Nevertheless, Adhami et al. (2018) asserted that ICO terms, marketing, bonus schemes are only fractionally significant for the chance of success of ICO but presale appears strongly and positively related to the probability of ICO success. In summary, Table 7 represents variables that are mostly used by researchers who analyzed aspects related with ICOs. Table is break down into four different categories, which are divided in accordance to the analyzed research problems: motives to invest and geographical distribution, success factors of ICOs, market cycles as well as underpricing in ICOs. Moreover, dependent variables (if applicable) and predictors are distinguished as well. Authors who investigated grounds to invest into ICOs (e.g. Fisch et al., 2019) used variables such as equity stake, financial gains, technology importance, sociodemographic motives, etc. The factor analysis was incorporated and regression analysis was established to identify the correlation between different motives. Huang et al. (2019) analyzed geographical distribution and different ICOs prevalence among countries. Researchers mostly used variables that are related with equity market development level (e.g. equity market index), banking industry (banking index), legal aspects (e.g. tax burden), crowdfunding development and prevalence (e.g. venture capital availability, the amount of crowdfunding platforms). Towards the geographical distribution, GDP per capita mostly is used as control variable.

Moreover, many substantial forces constantly increase the demand for blockchain – based early funding. ICO campaigns provides entrepreneurs with the possibility to induce buyer competition for the token by giving it value. For instance, Catalini and Gans (2018) indicate that mainly initial funds raised are maximized by setting growth rate to zero in order to lead saving by early birds.

Table 7

Variables used in researches that analyses ICO related aspects

TARGET	PREDICTORS/VARIABLES	YEAR	AUTHORS
	MOTIVES TO INVEST AND GEOGRAPHICAL DISTRIBUTION		
Post-ICO market performance (BHAR)	Institutional investor backing. **Control:** *token supply, presales, free tokens, investor restrictions, team size; platform, GitHub, technical team members.*	2020	C.Fisch; P.P. Momtaz
Ideological, Financial, Technological motives to invest	Utility (functions of tokens), Social (sustainability), Disruption (decentralization, anonymity), Technology, Sale (long and short term), Equity stake, Financial gain, Sociodemographic (age, level of education, residence, etc.)	2019	C. Fisch; C. Masiak; S. Vismarac; J. Blocka
Number of ICOs per country or total fund raised in particular country	Banking Index, Equity Market Index, VC Index, ICO Regulation, Crowdfunding Platforms No. **Control:** *GDP per Capita, Density, Financial Market, Development Index, Access to Banking, Venture Capital Availability, Tax Burden, country risk*	2018, 2019	J. An; W. Hou and X. Liu; W. Huang; M. Meoli; S. Vismara
	SUCCESS FACTORS OF ICOs		
Total money raised of asset in crowd sale	Availability of white paper, Technology relevance, Legal relevance of white paper, Availability of open source code, Total commit number of open source code for asset. **Control:** *Types of tokens issued, project team size, industry of an ICO project, market environment*	2019	K. Chen
ICO Success (when soft-cap is reached)	Code availability, White paper availability, Presale, Bonuses, Type of issued tokens **Control:** *Jurisdiction, volatility of Bitcoin and Ether*	2018	S. Adhami; G. Giudicib; S. Martinazzi
	MARKET CYCLES		
-	Cumulative amount raised in ICO campaigns, Price of Bitcoin, Price of Ether	2019	Christian Masiak & Joern H. Block & Tobias Masiak Matthias Neuenkirch & Katja N. Pielen
	UNDERPRICING IN ICOs		
The level of underpricing	Trading volume issue size, Issuer retained ratio, Coins sold ratio, Hot market, Pre-ICO, Bonus scheme, Type of tokens issued	2019	Thomas Heine Felix, Henk von Eije
Underpricing	Crypto news, Tweets, Threads, Followers. **Control:** *Min cap, Max cap, ICO duration, Raised funds, Firm age, Crypto news, Raised funds*	2018	Mathieu Chanson, Jonas Gjoen, Marten Risius, Felix Wortmann

Source: Compiled by an author in accordance

Additionally, Adhami et al. (2018) recognized that ICO success probability increases by attracting initial market interest enough for early funding. Equally important is the structure of an

ICO that is also consider having an influence on token sale's project success. For example, the existence of presale or bonus scheme could affect the likelihood of success by increasing initial market interest or attracting interested individuals to collect enough early funding to generate momentum for the ICO (Adhami et al., 2018).

Since ICOs are characterized with a high information asymmetry, participants rely on a very narrow collection of information (Chen, 2019). Usually, the main document disclosed for ICO project is called "white paper". Some of these documents are more technical and detailed than others. Therefore, an easily available and fulfilled information regarding ICO project is considered to positively influence the probability of a project's success. However, Adhami et al. (2018) argued that success is not affected by the availability of "white paper" but is strongly affected by the set of codes introduced for the ICO project. Open-source codes help to pre-estimate the technical soundness and the real state of the ICO. Therefore, the information provided in "white papers" are not valued buy the potential contributors of ICO campaign. Fisch (2019) agrees with the statement that increased amount of funding is highly related with the quality of code of ICO project. In addition, researcher indicates that success in ICO is associated with credible commitment to the ICO as well as quality signals.

The most widely examined topics in regards of ICOs are legal and regulation aspects as well as ICOs success. In most cases where success factors and value determinants of ICOs were investigated (Chen, 2019; Amsden et al., 2019; Catalini et al., 2019; Adhami et al., 2018) total money raised in token sale and ICO success (binary data) were chosen as dependent variables. Usually, to be successful, company must satisfy one main assumption – to reach predetermined soft-cap. In regards of predictors, the variety depends on the design of the research. The most used variables for more technology-oriented analysis are the availability of white paper, technology relevance, availability of open source code, soft cap, pre-ICO duration, ETH volatility, pre-ICO, bonus scheme, etc. Chanson et al. (2018) used crypto news, tweets, threads, and followers to analyze the level of underpricing.

As already discussed in this chapter, in the past couple years ICOs have received great attention as a novel way of crowdfunding. Due to rapid growth, ICOs have become a noticeable topic for academic research. Inquiries of ICOs include many different factors and methods depending on the design as well as the aim of the investigation. However, the extent of analyses of ICOs is rapidly increasing and researchers have already introduced important insights.

2 METHODOLOGY OF ICO CROWDFUNDING AND POST-ICO TOKEN MARKET PERFORMANCE ANALYSIS

The second chapter of the research describes the structure and the process of the two quantitative statistical research models by providing a detailed plan of methodology (section 2.1). This section includes the construction and substantiation of methods that were applied. Thereby, an essential effort has been made to prepare a methodology for sound and reliable twofold analysis. Therefore, various methods and variables that were commonly used by researchers in related scientific literature (section 1.3) are strongly considered while preparing methodology for this research. Based on data availability, examined literature, and trends in empirical financial studies, WLS Multiple Regression and Vector Autoregression methods are considered as the most suitable way to examine blockchain-based token sale process. This chapter begins by introducing the overview of the research structure and by providing visual scheme of the prepared methodology. The subsequent sections 2.2 and 2.3 impart construction of separate research models (WLS Regression and Vector autoregression) by providing justification, assumptions, formulas, variables, samples, time horizons, and hypotheses of each method.

2.1 The Overview of the Research Structure for Analyzing ICO Process

The methodology of this research includes two types of quantitative analysis models as the whole research is divided into two main parts: ICO crowdfunding stage and post-ICO token market. The visual scheme of the research is introduced in Figure 3, which provides generalization of overall methods used. Each component of the methodology is briefly presented further below.

The first part of analysis employs Weighted Least Square Multiple Regression with the purpose to analyze the relationships between dependent variable (total funds) and predictors. This model focuses on the ICO crowdfunding stage with the intent to examine what factors affects higher ICO gains. First model's development starts with predictor selection based on analyzed literature, sample size determination, data sampling and collection. As identified in Figure 3, all predictors are classified in three groups: financial, technical and predetermined ICO characteristics. In addition, model is hypothesized based on the different groups of predictors. Moreover, regression analysis consists of assumption testing by using tools such as Kendall correlation matrix, scatter plots, VIF, etc. In connection, to check model suitability and reliability, ANOVA analysis, descriptive statistics, Mahalanobis distance (detection of outliers) and R^2 are employed.

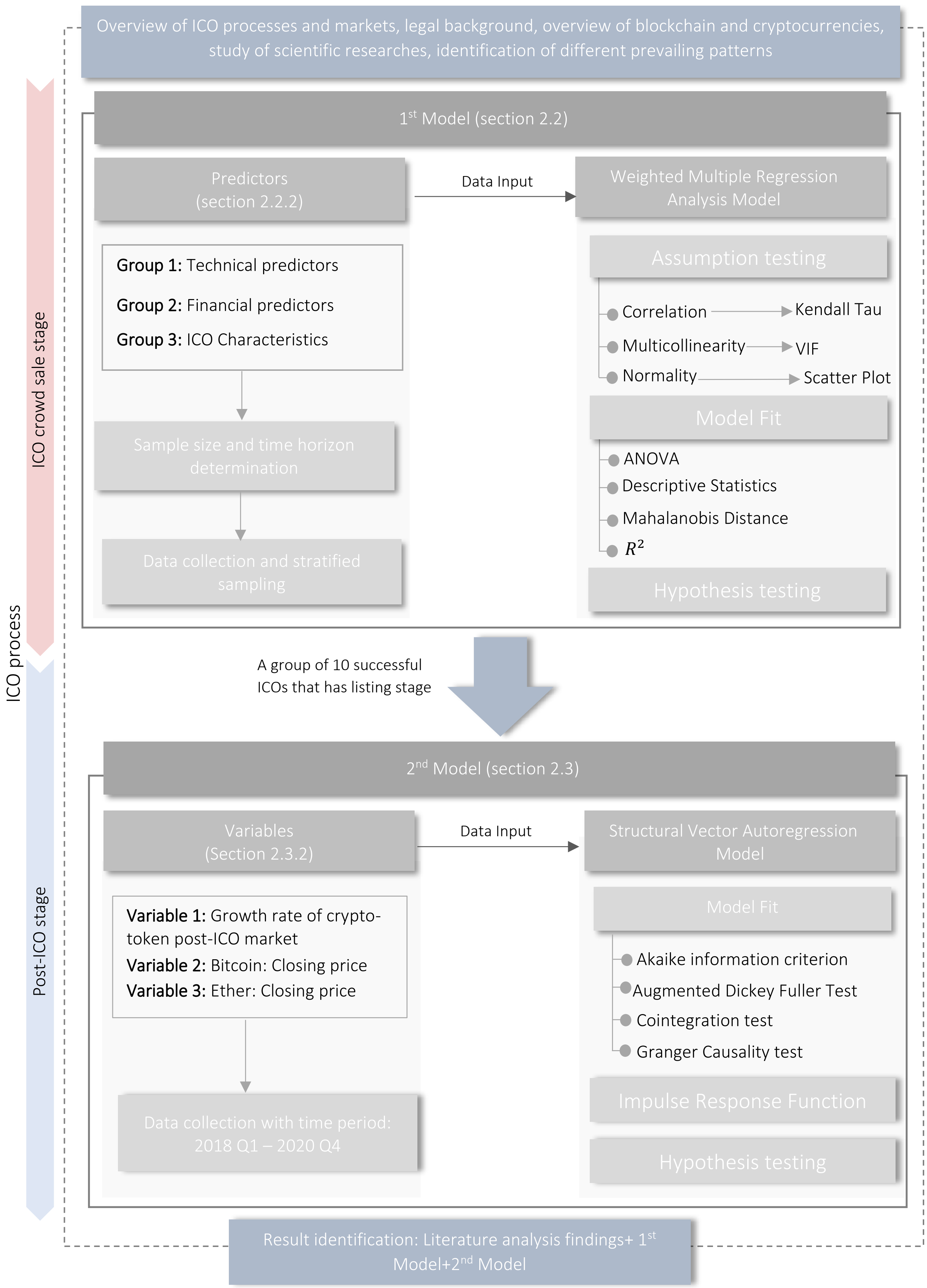

Figure 3. Structural Visualization of the Research Analysis

Source: Prepared by an author

The second part employs Vector Autoregression Analysis (VAR). The focus of the latter model is to investigate how listed tokens of successfully completed and the most valued ICOs (taken from the first part of the analysis) are affected by the two main cryptocurrencies with the highest market capitalizations. VAR analysis is used to examine orthogonal shocks in post-ICO market. Therefore, three variables are included into analysis: average weekly price of Bitcoin, average weekly price of Ether, and weekly growth rate of post-ICO market, which is calculated based on aggregate market capitalization from the group of projects taken from 1st analysis model. Therefore, 2nd model includes only the most valued and fully completed projects with secondary market trading possibility. The main question analyzed in the second part: does price shocks exist in the altcoin market when shocks appear in Ether and Bitcoin markets. Therefore, VAR is chosen as this research 2nd model to describe dynamic behavior of crypto-market time series. In the literature VAR is described as one of the most flexible models of multivariate analysis. This model is implemented by using Granger causality, Augmented Dickey Fuller Test (ADF) for stationarity testing (as in VAR all variables have to be stationary), Akaike information criterion to define optimal variable lags, etc. In addition, in order to make conclusions and to identify shock in the dataset, Impulse Response Function is incorporated. Further representation is identified and all formulas of 2nd model are explained in section 2.3.2. Finally, the results are composed of literature analysis, the 1st model and the 2nd model findings.

2.2 Methods for ICO Crowdfunding Stage Analysis

This section begins by providing comprehensive overview of the 1st analysis model. A lot of attention is given for assumption testing, qualitative data collection, and dataset suitability checking for WLS Multiple Regression analysis by using various statistical tests. The subsequent section also provides the description of independent and dependent variables, sampling techniques, and sample size estimation. Moreover, the 1st model of the research is hypothesized by using 3 different hypotheses based on different groups of predictors, presented at the end of this section.

2.2.1 The Construction of Weighted Least Squares Multiple Regression Method

Weighted Least Squares Multiple Regression analysis was selected to evaluate the influence of chosen predictors for total fundsraised in ICO and to examine main factors that cause higher ICO profitability. This research method was chosen because ICO historical data is short and values of dependent variable have great differences, dataset violates homoscedasticity assumption. WLS regression attributes each observation with a weight that is based on the variance of its fitted value hereby reducing the sum of the weighted squared residuals and eliminating the heteroscedasticity (Garson, 2013). WLS regression can be used for linear as well as nonlinear data in the parameters and it is an efficient technique for small data samples. The biggest advantage of method is that it can handle the data points of varying quality (Croarkin et al., 2006). In accordance to Zaid (2015), regression methods are one of the mostly used statistical processes in behavioral and physical sciences. As literature describes (Whitcomb, 2012; Yan and Su, 2009, Zaid, 2015) Multiple Regression analysis is the statistical method for investigating the relationships between two or more variables that have reason and result relation. Generally, Multiple Regression is used to find the effect of outcome while accounting for more than one factor that could influence the dependent variable (Yan; Su, 2009). In addition, Whitcomb (2012) explains further that the regression method determines the latter relationships to respond to the query of how much the response variable alters with occurred changes in each of the explanatory variables. In addition, to establish sound analysis model, all steps were be recognized and introduced below:

(1) To estimate sample size and chose the most appropriate sampling technique;

(2) To collect and compute data from reliable sources;

(3) To formulate null hypothesis and alternative hypothesis on population parameters;

(4) To define a decision rule to reject or not to reject the null hypothesis;

(5) To test assumptions for model suitability;

(6) To develop a model;

(7) Interpret the findings in accordance to the prepared methodology.

It is important to mention that regression analysis was hypothesized and based on assumptions that were introduced in the literature (e.g. Zaid, 2015; Pallant, 2010; Garson, 2013; Whitcomb, 2012). The hypothesis formulation implies decision making on the basis of sample data. The decision was made on to reject or not to reject that certain limitations were satisfied by the basic model premises. Following fourth step, assumptions identified in 2.3.2 should be satisfied in order to establish research model and confirm/reject hypotheses.

The relevancy of the regression analysis and statistical tests of the observations' ability to predict the outcome variable and WLS model was estimated using software "R" as the main tool. SPSS was used as additional program to remove outliers.

2.2.2 Predictors, Hypotheses and Assumptions of ICO Crowdfunding Stage Analysis

Data and time horizon of the ICO crowdfunding stage was selected in accordance to the analyzed literature (Chen, 2019; Fish, 2019; Huang, 2019; Amsden and Schweizer, 2018; Adhami et al., 2018; Masiak et al., 2019; Felix et al., 2019; Chanson et al., 2019), where hypothesis was made in accordance to the design and aims of the research. Each of the aspects are discussed further below.

Time Horizon. The first ICO was initiated in 2013, however, only in 2017 distributed blockchain-based token sales started to increase by gathering more attention from society and investors. As the phenomenon of ICOs is new, the time horizon of the research lacks long-time data. However, the extent started to increase from 2015, with this intention, data for the model was collected in a period from 2014 to 2020, where the most cases where taken from year 2017 and least cases exist in 2015 (only 2 projects). As a result, the period of the regression analysis model is 5 years.

Sample size. The amount of observations in the dataset was calculated by using G*Power software. Under the confidence level of 95% (as this is the standard of empirical researches), the minimum required sample size was calculated to be 110 (Figure 4).

However, in order to conduct more reliable research model, 217 observations were included into WLS regression. Although, some observations were removed while implementing the model (described further in the research). Only completed ICOs were included in the analysis due to lack of information and records of incomplete projects. In addition, failed ICOs did not fulfill the criteria to be selected for this analysis.

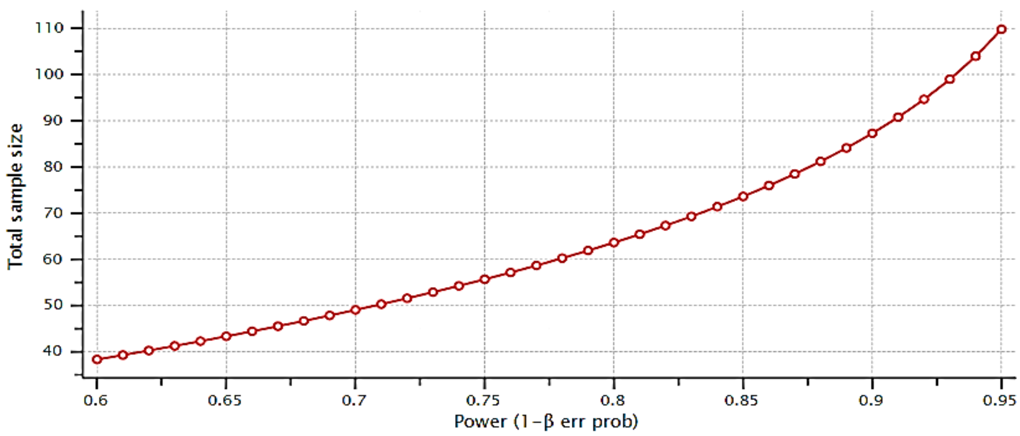

Figure 4 Minimum Required Sample Size with Confidence Level of 0.95

Source: Prepared by an author using G*Power software

As calculated minimum sample size was 110 out of 614, projects were chosen by using stratified random sampling which is one of the probability sampling techniques. Firstly, in stratified sampling, the population was divided into homogeneous groups (called strata) based on particular characteristics, and a sample was randomly taken from each strata (Ackoff, 1953). The 614 projects were divided into 7 groups under the amounts of funds raised and 31 project were randomly selected from each stratum (Table 8).

Table 8

Stratified Random Sampling: Ranges for ICO Project Selection

STRATA	RANGE OF COLLECTED AMOUNTS
Group I	> 50 000 000 USD
Group II	50 000 000 USD – 30 000 000 USD
Group III	30 000 000 USD – 20 000 000 USD
Group IV	20 000 000 USD – 10 000 000 USD
Group V	10 000 000 USD – 5 000 000 USD
Group VI	5 000 000 USD – 1 000 000 USD
Group VII	<1 000 000 USD

Source: Prepared by an author

This approach was applied in order to include all important sub-population into the model (Taherdoost, 2016) to have all levels of projects for precise analysis.

Predictors. Most common regression analyses include two types of variables: dependent variable and predictors. In particular, this multiple regression analysis model consists of one dependent variable (total funds raised identified in Table 9) and 15 predictors (Table 10).

Dependent Variable: total funds raised is depended variable of this research, which stands as the measure of how tokens are valued in the ICO market. This variable was chosen because of analyzed literature as the most suitable parameter, considering design and objectives of the research. Explained variable is expressed in U.S. dollars and is continuous.

Table 9

Dependent variable of Regression Analysis Model

VARIABLE	DESCRIPTION
T_FUND_RAISED	Variable presents the total amount (USD) that is raised during the crowdfunding stage

Source: Prepared by an author

Independent Variables: Independent variables were break down into three groups: financial and technical variables as well as predetermined ICO characteristics. Financial group of variables consists of hard cap, minimum contribution size, and soft cap (determined or not). Initial ICO characteristics that might have significant influence on total funds raised are token type, total supply of issued tokens, publicly available token supply (estimated in percentage), pre-sale existence, bonus scheme availability, and ICO duration. The last group of predictors includes white paper availability, open-source code availability, and criteria, which determines whether particular ICO accepts cryptocurrencies, fiat money or both as a payment. Every group of predictors where composed in regards of analyzed literature, based on the common trends in the market, as well as considered by an author while following ICO investor news.

Table 10

Predictors of Regression Analysis Model

VARIABLE	DESCRIPTION	TYPE
	FINANCIAL	
HARD_CAP	Hard cap – maximum amount that can be collected in ICO crowdfunding (USD)	Continuous
MIN_CONTR	Minimum allowed contribution in ICO crowdfunding (USD)	Continuous
SOFT_CAP	If soft cap (minimum amount required to complete the project) of ICO is reached	Binary
	ICO CHARACTERISTICS	
TYPE_TOKEN	Type of tokens issued in ICO (utility or other)	Binary
T_SUPPLY	Total supply of issued tokens in ICO (units)	Continuous
PUB_SUPPLY_PERC	Supply available for investors in ICO crowdfunding (%)	Continuous
PRE_SALE	Pre-sale availability in ICO	Binary
BON_SCH	Bonus scheme availability	Binary
ICO_DUR	ICO duration (time period between start of token issue and end/listing stage)	Continuous
	TECHNICAL	
WHITE_AV	White paper availability	Binary
OPS_COD_AV	Open source code availability	Binary
OWN_BLOCK	If ICO is based on own blockchain or on already existing (usually Ethereum)	Binary
CRP_ACC	If ICO accepts cryptocurrencies	Binary
FIAT_ACC	If ICO accepts cryptocurrencies fiat money	Binary
BOTH_CURR_ACC	If ICO accepts both types of payment (cryptocurrencies and fiat money)	Binary

Source: Prepared by an author

Dependent variable as well as 5 predictors (hard cap, minimum contribution size, total issued supply, public supply, and ICO duration) are continuous (has an infinite number of possible values (Whitcomb 2012)). Other 10 independent variables are categorical variables (has value of 1 or 0). For each project information is collected from Token data (tokendata.io); ICO Drops (icodrops.com); ICO rating (icorating.com); and open source code has been found on Github (github.com).

Assumptions. In statistical models, parametric indices deliberate some certain characteristic about the data, model suitability as well as reliability. The nonconformity of assumptions could cause inaccurate interpretation of the findings. In some cases, exceptions might be made but must be highly substantiated. In accordance with the analyzed literature, assumptions tested are underlined and explained below (Zaid, 2015; Pallant 2010; Whitcomb 2012):

1st Assumption. Correlation: (1) in the underlying time series process, none of the independent variable has a perfect linear combination with each other; (2) the dependent variable and predictors should be highly correlated, while the relation between predictors must have weak correlation coefficient. Kendall Correlation is applied to the model because data sample is not large, some outliers might exist, and has intuitively simple interpretation (Noether, 1981).

2nd Assumption. Normally distributed errors: it assumes that the residuals in the model are normally distributed with the mean of 0. The difference between the model and observed data are most frequently zero or very close to zero. Moreover, WLS regression is sensitive to the outliers that has to be tested and in order to avoid negative impact on the model estimation (Croarkin, 2006). Generally, the normality assumption can be measured by scatterplots. Graphical methods provide information about the shape of the distribution whether the data is normally distributed or not, as well as if it has outliers.

3rd Assumption. The significance of the results (model fit) should be tested. Therefore, ANOVA is used and below hypotheses are concluded:

$$H_0\colon\ \beta_1 = \beta_2 = \cdots = \beta_n = 0 \qquad (1)$$

$$H_A\colon\ \beta_j \neq 0; j = 1,2, \dots, n \qquad (2)$$

Null hypothesis indicates that all β_j are equal to zero and there is no statistical significance in the model. While alternative hypothesis states that at least one β_j is not equal to zero and is significant.

4th Assumption. No multicollinearity: predictors of the model are not highly correlated with each other. If the analysis includes more than one independent variable, it could cause the concern of multicollinearity, when there is a strong correlation between two or more predictors. At any cases, when multicollinearity occurs, it produces three main problems:

1. Unreliable β coefficients;
2. Multicollinearity limits R coefficient, which is a measure of the correlation between the predicted value and the observed value.
3. Multicollinearity between predictors limits the assessment of the individual importance for each variable.

The 3rd point is checked by Variance Inflation Factor (VIF) coefficient, which, according to Sheather (2009) should be less than <5.

5th Assumption. The dependent variables have interval or ratio level.

6th Assumption. The explained variable is uncorrelated with the error term.

However, assumptions are compounded in a general way; consequently, some of them can be ignored or modified depending on the type of the analysis, data and time interval. Each assumption is tested and confirmed, rejected, or violated as indicated below (if the decision is made to ignore assumption, it is reasoned by theory in literature):

Perfect correlation, strengths and direction of correlations. The Kendall Correlation introduces a sample correlation coefficient (r), which estimates the direction and the strength between pairs of variables. When the coefficient is near to 1, it indicates that there is a strong relationship between the pair of variables and that the variation in one variable is highly correlated with the changes in the other. When the coefficient has a value near 0, it means that variables are not highly correlated with each other. The correlation between dependent variable and predictors must be high to confirm that independent variable has the ability to influence the Y (coefficient r >0.3), whereas X variables must be weakly correlated (r <0.7) (Pallant, 2010).

Moreover, the influential points can greatly affect the slope of the WLS regression function, therefore, it is important to detect outliers from the sample. The robustness regression model was considered as one of the solution for skewed data analysis. However, it was not applicable due to singularity issue as many categorical independent variables were included into analysis as predictors. Wherefore, squared Mahalanobis distance approach was selected as the most suitable classical way for multiple linear regression model (Rousseeuw & Leroy, 2005). Squared Mahalanobis distance formula is as per below (Ruginski, 2016):

$$D^2 = (x - m)^T \times C^{-1} \times (x - m) \quad (3)$$

Where:

- x is the vector of the observation (the row in a dataset);
- m is the mean values of predictors (the mean of each column);
- C^{-1} is the inverse covariance matrix of predictors.

Mahalanobis distance is a multivariate distance metric that estimates the range between a point and a distribution (Ruginski, 2016). In accordance to the latter author, Mahalanobis distance is a highly applicable measure for insanity detection, classification of highly imbalanced datasets and other unfitted cases.

Hypotheses of the study. The 1st research model was hypothesized in order to compose structured analysis and substantiated conclusions. For this research, the general hypothesis was expressed in the theoretical way, to test who determines the value of ICO project in crowdfunding stage. The main aspiration was to identify how predictors will influence the dependent variable: the chosen predictors can explain how much the variance in the total funds raised. Three hypotheses of the analysis were formed as follows:

1) The first one is in regards of 1st group of variables:

H_1: Financial determinants do have significant influence on the total funds raised in ICO crowdfunding stage;

2) The second one is in regards of 2nd group of variables:

H_2: Initial ICO characteristics do have significant influence on the total funds raised in ICO crowdfunding stage;

3) The third one is in regards of 3rd group of variables:

H_3: Technological aspects do have significant influence on the total funds raised in ICO crowdfunding stage.

The general hypothesis was checked after testing all assumptions whether the method of the analysis was recognized as suitable for the particular analysis. Besides, this model includes several additional hypotheses for assumption testing and determination of suitable parameters.

When all assumptions were confirmed, model equation was concluded. The basic presents of the WLS regression model formula is as per below. 4th for formula is the general multiple regression model.

$$Y_i = \beta_0 + \beta_1 X_i + \ldots + \beta_n X_n + \varepsilon_i \quad (4)$$

Where:

β_0 – intercept of Y;

β_n – coefficient;

X_i – predictor;

ε_i – residual ~ $N(0, \delta^2/w_i)$.

The WLS estimates of $\beta_0$and β_n:

$$Sw(\beta_0;\, \beta_n) = \sum_{i=1}^{n} w_i(y_i - \beta_0 - \beta_n X_1)^2 \tag{5}$$

Where w_i are inversely proportionate: (1) data points with lower variation were assigned higher weights; (2) data points with higher variation were assigned with lower weights. Then WLS is given as:

$$\beta_0 = \overline{y}_w - \beta_1 \overline{x_w} \tag{6}$$

$$\beta_1 = \frac{\sum w_i(x_{i-}\overline{x}_w)(y_i - \overline{y}_w)}{\sum w_i(x_i - \overline{x}_w)^2} \tag{7}$$

Where $\overline{y}_w$ and $\overline{x}_w$ are the weighted means (*source*: mcmaster.ca).

As a methodology for the 1st model is already discussed, the realization of the WLS Regression analysis for analysis of elements determining higher gains in ICO in crowdfunding stage is presented in chapter 3.1

2.3 Methods for Post-ICO Token Market Performance Analysis

The section starts by providing a comprehensive overview of the 2nd analysis model. This model aimed to analyze and investigate post-ICO market performance based on shocks appearing in Bitcoin and Ether markets. Throughout this section, basic points were to introduce the Vector autoregression method by substantiating its suitability and providing sequential steps that should be implemented in chapter 3.2. Moreover, this section also outlines variables, time horizon, and hypotheses that were used to implement the 2nd model of the research.

2.3.1 The Construction of Structural Vector Autoregression Method

Vector autoregression was chosen as second part analysis model because it examines joint dynamics of multiple time series and is considered in the analyzed literature towards ICOs (chapter 1.3.2). Some authors (e.g. Richards, 2005) emphasizes that VAR is one of the most flexible models of multivariate time series analysis. It is noticed in the literature, that especially VAR models are useful in order to describe dynamic behavior of economic and financial time series. Moreover, to examine interactions between variables in a dataset, two approaches can be used: VAR with minimal restrictions and VAR with applied theoretical restrictions. The main difference between Multiple Regression analysis and VAR is that in regression, predictors are added to the model by assuming that they are fully independent and each variable explains variance in dependent variable as a unique function. In VAR models all variables are added the same way: each component in the analysis has an equation based on its own lagged values as well as other variables lagged values by explaining equation evolution. In this research model, the aspiration is to investigate cryptocurrency market shocks from observables by introducing minimum possible assumptions that are compatible with a large class of models. As Keating (1992) states, VAR models are general dynamic specification because each variable in the model is a function of lagged values of all other variables in the model. The traditional VAR model could not be applied in this analysis due to the problem with least squares estimation, which implies the possible correlation between error terms. By employing VAR without the transformation to structural VAR, it is difficult to examine the true innovations and pure shocks (Masiak et al., 2019). Structural VAR of three variables can be represented by using below formula:

$$AX_t = \beta_0 + \beta_{t-1}X_i + u_t \tag{8}$$

Where:

- X depends on lag of itself and structural shocks (independent from each other).

As this model has three time series (post-ICO market growth rate (Y_t), daily closing price of Bitcoin (BP_t) and daily closing price of Ether (EP_t) the system of the equations: X=$\begin{pmatrix} Y \\ BP \\ EP \end{pmatrix}$ is express as per below (system of equations where each equation is written per each variable) :

$$Y_t = \beta_0 + \beta_{11,1}Y_{t-1} + \beta_{12,1}BP_{t-1} + \beta_{13,1}EP_{t-1} + u_{1,t} \tag{9}$$

$$BP_t = \beta_0 + \beta_{21,1}Y_{t-1} + \beta_{22,1}BP_{t-1} + \beta_{23,1}EP_{t-1} + u_{2,t} \tag{10}$$

$$EP_t = \beta_0 + \beta_{31,1}Y_{t-1} + \beta_{32,1}BP_{t-1} + \beta_{33,1}EP_{t-1} + u_{3,t} \tag{11}$$

Where:

- Y_{t-1}, BP_{t-1}, EP_{t-1}, are the lag of time series Y_t, BP_t, EP_t respectively;
- $u_{i,t}$ – structural shocks.

In VAR models every variable is designed as a linear combination of past values - variable itself and other variables that are included in model dataset (Prabhakaran, 2019). The reduced form of the VAR model can be estimated by multiplying equation be inverse of matrix A:

$$A^{-1} \times AX_t = A^{-1} \times \beta_0 + A^{-1} \times \beta_{t-1}X_i + A^{-1} \times u_t \tag{12}$$

As a result, final reduced formula is as per below:

$$X_t = G_0 + G_1 X_{t-1} + \varepsilon_t \quad (13)$$

Where:

- X_t is the vector of variables;
- G_0 is equal to $A^{-1} \times \beta_0$;
- G_1 is equal to $A^{-1} \times \beta_1$;
- Forecast error ε_t are equal to $A^{-1} \times u_t$.

Moreover, matrix A relates the errors (ε) of the reduced VAR form and shocks (u_t). The errors (ε_t) are the linear combination of structural shocks (u_t). The reduced VAR cannot be estimated directly, therefore, to get structural equation, matrix A must be calculated. Afterwards A should be multiplied by reduced-form VAR to get structural model, shocks and contemporaneous relationships between variables in the dataset (Prabhakaran, 2019, Gottschalk, 2001, Ouliaris et al., 2016). Also, Keating (1992) identifies that set of used variables in the model could not be too large, since each equation has a lot of lags of each variable. Therefore, the set of data for this analysis was reduced to 3 different components (average weekly price of Bitcoin, average weekly price of Ether, and weekly growth rate of post-ICO market). Moreover, large dataset in VAR model could cause multicollinearity issue, loose degrees of freedom as well as statistically insignificant coefficients. Similar analysis was made by Masiak et al. (2019) where author pursued to examine market cycles of ICOs. However, this research includes the study of the relationships between altcoin market and two main currency markets (Bitcoin and Ether). ICOs that have listing stage and were recognized to have valuable ICO characteristics were included as variables in VAR. Variables and other components of VAR analysis were introduced in the next section.

2.3.2 Time Period, Variables and Hypotheses of Post-ICO Token Market Analysis

The procedures of handling the data followed the suggestions of analyzed literature (Fish, 2019; Adhami et al., 2018; Masiak et al., 2019) and the data availability. Variables were sorted out in accordance to the 1st analysis model: projects that have characteristics of valuable ICO were included in the 2nd model. Moreover, time horizon was chosen to correspond to the listing period of selected variables (listing starts differ for each project). In addition, model was hypothesized in accordance to the design and aim of the research. Each component of VAR analysis is discussed below.

Variables. The 2nd model of the analysis is composed of three variables: average weekly price of Bitcoin and Ether; post-ICO market daily growth rate. The growth rate of post-ICO market consists of 20 ICO projects that have secondary market trading possibility, predetermined hard cap and open source code (sorted out in accordance to the 1st analysis model). The growth rate is calculated on the daily basis based on aggregate market capitalization. All variables are identified in Table 11.

Table 11

Variables for Structural Vector Autoregression Model

VARIABLE	DESCRIPTION	TYPE OF VARIABLE
BTC	The closing price of Bitcoin in a period 2018-2020	Continuous
ETH	The closing price of Ether in a period 2018-2020	Continuous
Y	The daily growth rate of post-ICO market 2018-2020 (composed of 10 ICOs)	Continuous

Source: Prepared by an author

Bitcoin and Ether was chosen because are declared as the main crypto-market components that could have substantial influence for altcoin market. The latter cryptocurrencies also have the highest market capitalizations. Token trading data was extracted from coinmarketcap.com by including closing prices (USD) and market capitalizations (USD) of listed coins/tokens.

Time Horizon. Bitcoin market has started to expand in 2013 and Ether market capitalization has started to increase in 2015. However, ICOs became popular later, therefore the time period of this model from March 6th, 2018 (when chosen ICOs started to list tokens) to November 23rd, 2020.

Hypotheses of the study. For the 2nd research model the general hypothesis was expressed in the theoretical way to test if shocks in post-ICO market exist due to the movements in cryptocurrency market. Since the focus of this model is successful ICOs that have listing stage, hypothesis was formed as follows:

H_1: Shocks in post-ICO market exist due to shocks in Bitcoin and Ether market.

As a methodology and other components of the 2nd model is already discussed, the implementation of the Structural Vector Autoregression model for token performance analysis in listing stage is presented in chapter 3.2.

2.4 Limitations of Data and Research Models

To appropriately generalize findings of the research, shortcomes should be identified. Therefore, this section gives an overview of the limitations of the research, which are mostly related to methodology and dataset.

The first limitation concerns data collection. As Initial Coin Offerings are newly arisen, there is lack of official websites where aggregate information is stored. As a result, data was collected from four different sources (Token data (tokendata.io); ICO Drops (icodrops.com); ICO rating (icorating.com); Coin Market Cap 9 coinmarketcap.com) and Github (github.com). The main sources were Token data (tokendata.io) and ICO Drops (icodrops.com), which are the most valued by the ICO contributors and founders. In addition, latter sources are considered as the most trustworthy ones. However, not all required information of particular ICO was provided in one website and information was collected from different sources for the same project (for instance, total supply was found on Token data (tokendata.io) whereas soft cap was taken from ICO Drops (icodrops.com), etc.). Due to the time differences of project listing on specific website, information provided might differ. Moreover, not all ICO projects can be disclosed in available sources. Due to some requirements or reference constraints, ICO projects can be omitted and not listed. As a consequence, this might affect the random selection of the dataset when stratified sampling technique was applied.

For second analysis model, the time period that was used in the model could be more extended. However, strict criteria was raised to the projects (e.g. projects have to be successfully completed; should have available open-source code; predetermined hard cap and secondary market trading possibility), which were selected to the second analysis model. With all parameters applied, time period between ICO campaigns highly varies (ones are listed later than the others or there was limited access to the required data). Therefore, it was difficult to find equal projects in terms of time horizon.

However, above listed limitations did not affect the credibility of the research models and interpretation of the results. For each model reliability and robustness tests were employed (normality, stationarity, multicollinearity, ANOVA, etc.), which indicated trustworthy outcome.

To sum up, methodology part covered the construction of two research models and helped to clarify the robustness tests that should be performed in order to compose reliable analysis. Moreover, this part also included explicit explanation and sequence of methodology application that is further used in chapter 3. Therefore, as methods, variables, dataset and samples, assumptions, robustness tests and limitations are examined and introduced, practical part can be implemented, results analyzed, outlook and recommendations proposed.

3 INVESTIGATION OF ICO CROWDFUNDING AND POST-ICO MARKET PERFORMANCE

As already discussed in earlier chapters, this research is based on two analysis models - each in different Initial Coin Offering stage. First of all, Weighted Least Square Multiple Linear regression analysis was applied to examine determinants, which influences higher gains in ICO crowdfunding stage and which are the most valued by ICO investors. The second Vector autoregression (VAR) model was applied in post-ICO stage to investigate the performance of listed tokens and to check if post-ICO market is affected by the shocks appearing in Bitcoin and Ether markets. A group of projects, that in 1st model were recognized as valuable between investors, were included in the 2nd model. The analyses are presented further below in a sequent order: (1) the progress and outcome is discussed of the 1st Model; (2) the implementation and results are analyzed of the 2nd Model; (3) after presenting both analyses separately, inquiries are consolidated by providing common discussion and outlook.

3.1 Investigation of ICO Crowdfunding Stage

WLS Multiple Regression analysis was chosen in order to check how well the group of selected independent variables (financial, technical, and predetermined ICO characteristics) are able to predict the stress levels of explained variable (total funds raised). The main aim of regression model is to investigate how much unique variance each of the predictor explains in the dependent variable over and above other predictors. Moreover, dataset suitability for chosen model must be tested and the regression analysis can be confirmed only when all assumptions (indicated in section 2.2.2) are justified. Therefore, the reliability and relationships between variables of the research were checked and verified by using Descriptive Statistics, Scatter plots, Variance Inflation Factor and Tolerance levels, Kendall correlation matrix, R squared, and ANOVA test. Model was implemented using “R” software and SPSS (for outliers’ detection and removal).

3.1.1 Examination of Elements Influencing ICO Crowdfunding Stage Gains

In the first place, overall 217 observations were gathered (estimated minimum sample size is 110), however, some data points were excluded from the sample while checking assumptions. The first assumption tested was normal distribution and linear relationship between dependent variable and predictors. Scatter plot was employed to check if data is linearly related and normally distributed. Scatter plot points should form an approximate straight line; any divergence from the straight line indicates deviations from normality. The result showed that sample was following linear relationship but some points were in great distance from the rest of the data (Figure 5). The graph gave the idea that some outliers exist in the data sample.

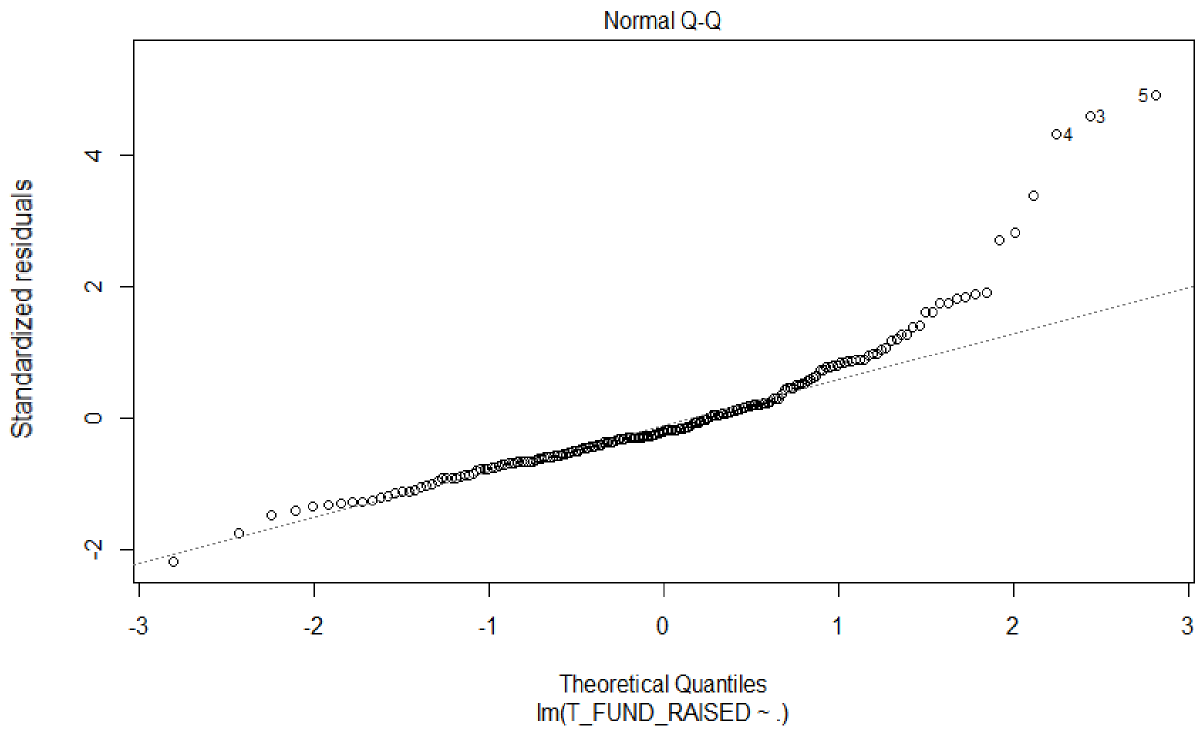

Figure 5. Scatter plot of Multiple Regression analysis model with outliers. Dependent variable: T_Fund_RAISED

Source: Prepared by an Author: R software output

Hence, it was decided to verify and remove outliers in the dataset with Mahalanobis distances (described in 2.2.2). After the Mahalanobis distance was applied, 16 observations were identified as influential points. Therefore, outliers were eliminated from the dataset and the regression equation was estimated without the influential points. The result is shown in Figure 6, which identifies that the linear relationship between variables exists but is not perfect: observations of the model are nearly spread to the line but there are some deviations. Skewed points specify that data set has some discrepancies, which identifies non-normality. Nevertheless, in real life, data usually is not normally distributed and this dataset is well suitable for chosen regression method. Moreover, as dataset of dependent variable has huge variation of values, Weighted Multiple Least Square Regression analysis with standard deviation function was chosen in order to avoid heteroscedasticity bias. As discussed in chapter 2.2.1, this method is well applicable for moderate datasets and provides optimized estimation as well as different types of statistical intervals.

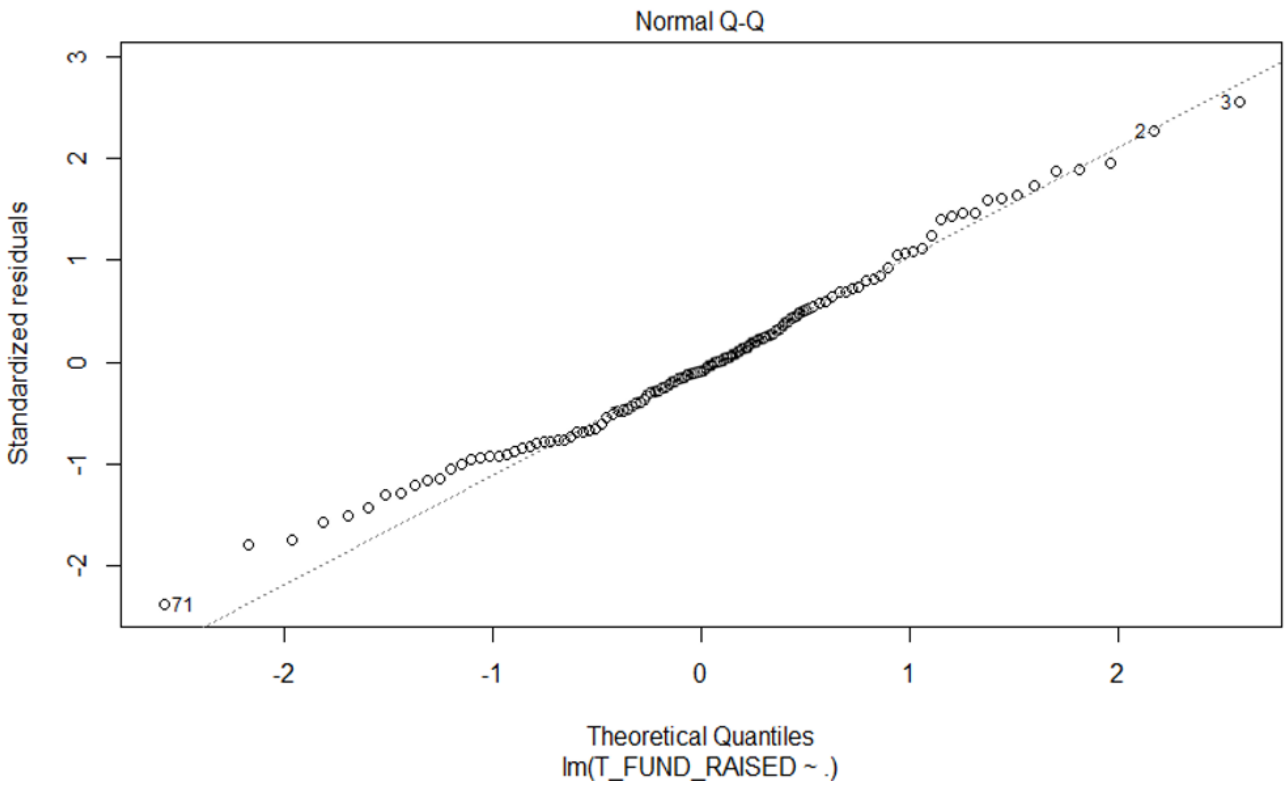

Figure 6. Scatter plot of Multiple Regression analysis model without outliers. Dependent variable: T_Fund_RAISED

Source: Prepared by an Author: R software output

After outliers were removed, overall 201 observations were included into the final model. As estimated minimum required sample size is 110, dataset is sufficient under 95 % of confidence level. Further, multicolinearity, model fit, and correlations can be examined as the normality of dataset was tested, outliers were eliminated and required sample size was satisfied.

Descriptive statistics. Table 12 describes variables by involving mean, standard deviation and total number of observations used in the model. The mean is the estimated central value of a group of numbers (the average) and standard deviation quantifies the variation (or dispersion) of dataset.

Not all predictors were included in the model. Variables excluded from the analysis as irrelevant for the model were: cryptocurrency acceptance in ICO as it does not have any correlation with dependent variable and ICO acceptance as it had the same correlation value as BOTH_CURR_ACC. All other predictors were considered to have the influence for total funds raised.

Table 12

Weighted Least Squares Regression: Descriptive Statistics

DESCRIPTIVE STATISTICS		
	Mean	Std. Deviation
T_FUND_RAISED	18149509.50	1.713
WHITE_AV	0.94	0.000
ICO_DUR	29.28	0.000
T_SUPPLY	4.3496730	2.9825170
PUB_SUPPLY_PERC	0.5295	0.00000
OWN_BLOCK	0.15	0.000
OPS_COD_AV	0.76	0.000
TYPE_TOKEN	0.95	0.000
BON_SCH	0.67	0.000
PRE_SALE	0.52	0.000
FIAT_ACC	0.14	0.000
CPRV_ACC	1.00	0.000
BOTH_CUR_ACC	0.14	0.000
HARD_CAP	16936498.22	1.784
SOFT_CAP	0.38	0.000
MIN_CONTR	97.3752	0.00003

Source: Prepared by an Author: R software output

The Table 13 shows how well gathered dataset fitted the analysis as it indicated the relationship between the group of predictors and the dependent variable. The explained variable's total variation was estimated by its variance. This proportion is expressed by adjusted R squared, which is 0.308. Adjusted R squared showed corrected value of the R Square, which provides better estimates for the true data set. The number indicates that 30.8 % of the variance in the total funds raised are explained by the regression equation of this model. The result is not very high but model is assumed to be valid as correlation between predictors and explained variable exists.

Table 13

Model Fit: Weighted Least Squares Regression

MODEL SUMMARY				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.653	.346	.308	1.476109

Source: Prepared by an Author: R software output

Moreover, ANOVA test was selected to check the significance of the results. Before completing the test, hypotheses were concluded (section 2.2.2). The null hypothesis indicates that all β_j are equal to zero and there is no statistical significance in the model. In contrary, alternative hypothesis indicates that there is a statistical significance in the model and at least one β_j is not equal to zero. In the output (Table 14) are seen that analysis has reached the required level of significance ($p<0.05$) and the null hypothesis can be rejected: at least one β_j is significant in the analysis model.

Table 14

Weighted Least Squares Regression: ANOVA Test (Prepared by an Author: R software output)

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	179.526	13	13.81	6.338	.000
Residual	407.454	187	2.179		
Total	586.981	200			

Source: Prepared by an Author: R software output

Further, as linearity and normality are confirmed as well as analysis summary indicated model feasibility and significance, correlations between variables may be examined. Correlations matrix (APPENDIX A) specified the strength and direction of relationships between variables. As it is identified in the methodology, the coefficient between explained variable and predictors must be more than 0.3, and between each pair of predictors less than 0.7. Variables that do not meet previous conditions must be eliminated from the model. The highest correlation coefficients between predictors are 0.483 and 0.478, which are not reaching the threshold of 0.7. However, to ensure that no multicollinearity issues exists, correlation was tested also by using Variance Inflation Factor and Tolerance (indicated in Table 15). The tolerance shows how much variability of the specified regressor is not explained by the other predictors. Value less than 0.1 indicates multiple correlations between variables. In addition, VIF exhibits multicollinearity if the value of coefficient is higher than 5. In accordance with Table 15, tolerance index is high for almost all independent variables and VIF coefficients are than 5. This only confirmed than none of the predictors should be eliminated from the model as no milticolinearity detected (assumption 4th in section 2.2.2 is substantiated).

Table 15

Weighted Least Squares Regression: Variance Inflation Factor Test

COEFFICIENTS		
Predictors	Tolerance	VIF
WHITE_AV	0.964	1.038
ICO_DUR	0.928	1.077
T_SUPPLY	0.978	1.022
PUB_SUPPLY_PERC	0.892	1.121
OWN_BLOCK	0.922	1.084
OPS_COD_AV	0.897	1.115
TYPE_TOKEN	0.950	1.053
BON_SCH	0.865	1.157
PRE_SALE	0.880	1.136
BOTH_CUR_ACC	0.915	1.093
HARD_CAP	0.885	1.130
SOFT_CAP	0.890	1.124
MIN_CONTR	0.847	1.181

Source: Prepared by an Author: R software output

Furthermore, the high correlation coefficient between explained variable and predictors had only two inputs: OPS_COD_AV (0.370; condition: >0.3) and HARD_CAP (0.419, condition: >0.3) (APPENDIX A). Therefore, only two variables can be assumed to have impact for total funds raised and those variables explain 30.8 % of variance in dependent variable.

Finally, all assumptions of the regression analysis were met and the model was described as trustworthy and reliable. Provided that analyzed measures indicated statistical significance of the model, hypotheses specified in part 2.2.2 should be revised. Considering that only operational code availability and predetermined hard cap were highly correlated with dependent variable, only 1st and 3rd hypotheses can be confirmed (see section 2.2.2). Therefore, hypotheses were summarized as per below:

1) Financial determinants have significant influence on the total funds raised in ICO crowdfunding stage.
2) Technological aspects have significant influence on the total funds raised in ICO crowdfunding stage.

The hypothesis in regards of ICO specialties has to be rejected, which identifies that there is no statistically significant influence of ICO characteristics for total funds raised (in this particular model of collected dataset).

Furthermore, after the hypotheses of the model were sorted out, final WLS equation can be written. Table 16 specifies coefficients (*β*), which shows how much each predictor gives unique contribution in explaining the dependent variable as well as establishes the strength and direction of each independent variable's influence. Only two variables that reached correlation threshold stated between independent and dependent variables (OPS_COD_AV and HARD_CA) were included in the final WLS equation. The Table 16 provides that the standardized coefficient (β_1) of Hard Cap is 0.3630 (Sig.= 0.0000) and has positive relation with Total funds raised of ICO in crowdfunding stage. Hard Cap was considered to have the highest influence for dependent variable as had the highest correlation coefficient (specified in Annex 1).

Table 16

Weighted Least Squares Regression: Coefficients

COEFFICIENTS						
	Unstandardized Coefficients		Sig.	Correlations		
	B	Std. Error		Zero-order	Partial	Part
(Constant)	22190184.5087	9623698.1168	0.0222			
WHITE_AV	-7391564.2501	5569121.0518	0.1860	-0.0470	-0.0966	-0.0809
OPS_COD_AV	3492349.7696	3174827.9942	0.0000	0.2696	0.2762	0.2395
T_SUPPLY	0.0001	0.0000	0.0516	0.1324	0.1418	0.1194
PUB_SUPPLY_PERC	-9620550.8425	5916369.6641	0.1056	-0.1784	-0.1181	-0.0991
OWN_BLOCK	-1461779.3060	3779001.3703	0.6993	0.0159	-0.0283	-0.0236
ICO_DUR	-174082.5643	44293.6652	0.2727	0.0607	0.0802	0.0670
TYPE_TOKEN	3559002.4226	5967758.5339	0.5516	0.0932	0.0436	0.0363
BON_SCH	-2663318.9048	2921045.7834	0.3631	-0.0762	-0.0665	-0.0556
PRE_SALE	875031.8973	2732378.6350	0.7491	0.1103	0.0234	0.0195
BOTH_CUR_ACC	6926504.6785	3885129.5238	0.0762	0.1696	0.1293	0.1086
HARD_CAP	0.3630	0.0622	0.0000	0.4185	0.3926	0.3557
SOFT_CAP	3146585.1148	2799608.3856	0.2625	0.1159	0.0819	0.0685
MIN_CONTR	139.2003	4484.1943	0.9753	0.0791	0.0023	0.0019

Source: Prepared by an Author: R software output

The standardized coefficient (β_2) of Open Source Code Availability is 3492349.7696 and has a positive relation as well as β_1. The latter predictor has lower correlation with the explained variable than Hard Cap. Nevertheless, unique contribution of the variance in the dependent variable is highly important and has statistical significance (Sig.=0.000).

WLS regression follows the dataset, which consists of the value of Y and values of two *X*. Consequently, equation that is useful for predicting the value of the dependent variable (*Y)* for given values of predictors (*X)*, was concluded below:

$$Y = 22190184.5087 + 0.3630X_1 + 3492349.7696X_2 \quad (14)$$

Where:

- An intercept (β_0)=1.473, which indicates value of the explained variable, when all predictors are (Operational code availability and Hard cap) are kept equal to 0.
- X_1 is Hard cap with β_1 equal to 0.3630, which shows by how much Total funds raised vary in the model when X_1 changes by one unit.
- X_2 is Open Source Code Availability with β_2 equal to 3492349.7696, which shows by how much Total funds raised increases when open source code of the ICO project is available for investors.

The principal findings of 1st Model, which analysed ICO crowdfunding stage were interpreted in the following chapter.

3.1.2 Interim Result Consideration of ICO Crowdfunding Stage Analysis

This research model uncovered characteristics that are most valued by ICO investors and predetermine higher gains in ICO crowdfunding stage. The key factors, in accordance to the first research model, are open source code availability as well as preset hard cap – the maximum amount of money that can be collected during the ICO crowdfunding. Moreover, the empirical analysis did not disclose that the higher gains in ICO crowdfunding stage are influenced by the availability of a white paper. White papers can be easily counterfeited and provide false and unreliable information, therefore it is not simply as valuable as, for instance, public open source code. The set of codes of blockchain project available for public is highly and positively valued by ICO contributors. In accordance to the empirical research, availability of code has statistically significant influence on total funds raised in ICO crowdfunding stage. Even the availability of partial set of code is assumed as proof-of-concept. However, latter aspect is more valued by the professional ICO investors, non-professionals mostly depend on white paper. Besides, the type of blockchain of the project is not considered as important characteristic in ICO mechanism as major part of blockchains are Ethereum and only few are unique (created own blockchain).

Moreover, research also revealed that predetermined total supply does not have influence for total funds raised but the part of supply that is available for public investors has a marginal importance. Due to the analysis, ICO project contributors appreciate more those projects that have greater part of token supply available for public in crowdfunding. Although, project funds raised does not rely on any pledged growth in the supply during particular time period.

Furthermore, bonus scheme is a part of marketing in ICO campaign as a way to attract contributors. The effect of different bonus schemes should be examined separately as in the pool together with other elements, bonus schemes do not have statistically significant impact for total funds raised. Pre-sale also does not have significant affection (only the modest) in this particular analysis even though pre-sales are described as valuable strategy to raise funds in ICO by checking market's readability. Although, as duration is also not one of the main characteristics that prescribes token success (as token value relies on a demand during a sole period of time), it could be assumed that marketing strategies have a major part in ICO project performance and must be examined individually.

Additionally, the 1st model of this research proved that hard cap helps investors to measure and foresee the ICO success. Therefore, contributors are tending to invest more in those projects that has predetermined maximum goal of investment. As contrary, based on research results, soft cap does not influence investors' decisions whether to invest or not.

Finally, the type of token (as major part of tokens are utility), both currency (cryptocurrency and fiat) acceptance as well as minimum contribution in this research has no effect on total funds raised. However, the requirement of higher minimum contribution can influence ICO projects prevalence by eliminating small contributors (which is the base for crowdfunding method of collecting funds).

3.2 Investigation of Post-ICO Token Market Performance

This part introduces analysis of the second research model, which pursue to examine post-Initial Coin Offering market performance. Particularly, Vector autoregression was employed to check how listed tokens perform in the secondary market and if there are any shocks related with Bitcoin and Ether market. The model was performed by applying several statistical test to estimate model fit as indicated in section 2.3.2. The main tests employed are Granger Causality test, Cointegration test, Augmented Dickey-Fuller, Schwarz (SC) criterion to define optimal variable lags. In addition, to identify and visualize results, Impulse Response Function was prepared. The results were obtained using software "Eviews" are presented in the following sections. Firstly, results of statistical tests are presented by providing tables and explanations. General interim results are analyze by using Impulse Response Function and discussed in section 3.2.2.

3.2.1 Examination of Structural Shocks in Post-ICO Token Market

The 2nd analysis model includes three variables: (1) weekly growth rate of ICO market capitalization of 10 ICOs that have listing stage, open source code, and pre-determined hard cap (called Y in the model); (2) average weekly price of Bitcoin (called BTC in the model); (3) average weekly price of Ether (called ETH in the model). Overall, 138 time series are used from 2018 Q1 to 2020 Q4. Figure 7 represents data Btcoin and Ether price changes that were included into the model.

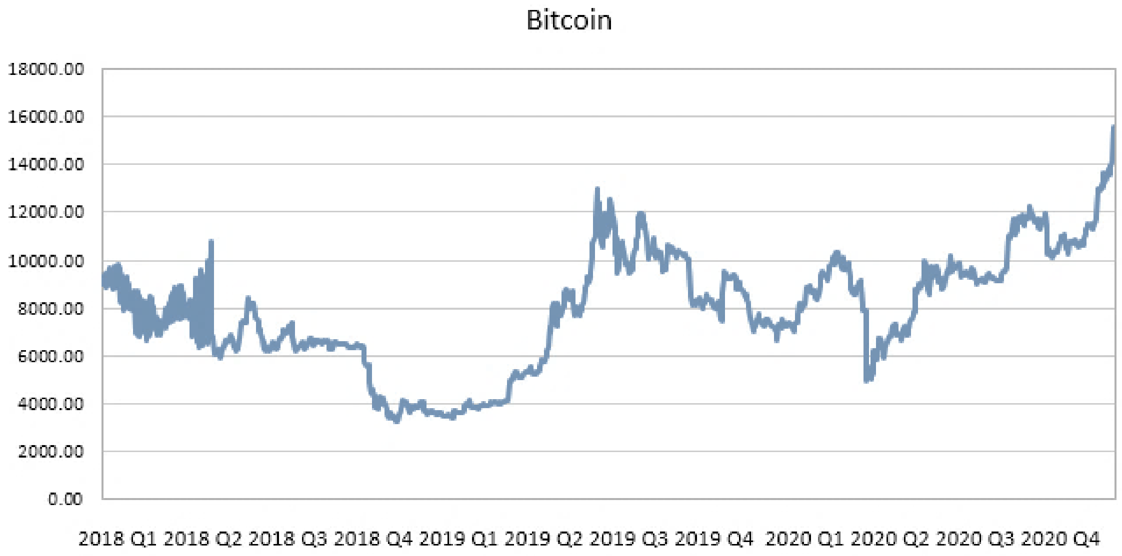

Figure 7. Price of Bitcoin and Ether in period from 2018 Q1 to 2020 Q4

Source: Prepared by an Author according to data from coinmarketcap.com

As can be seen from the graph, fluctuations are very high and frequent. Thus, it can be assumed that shocks in the market are persistent.

Figure 8 specifies changes in market capitalization of 10 altcoins that were selected as the most suitable to explore post-ICO market. Projects that awere included are as follow: Nebulas, Monetha, Everex, Viberate, SwissBorg, Fusion, We Power, Enjin Coin, Cryptopay, and Stream.

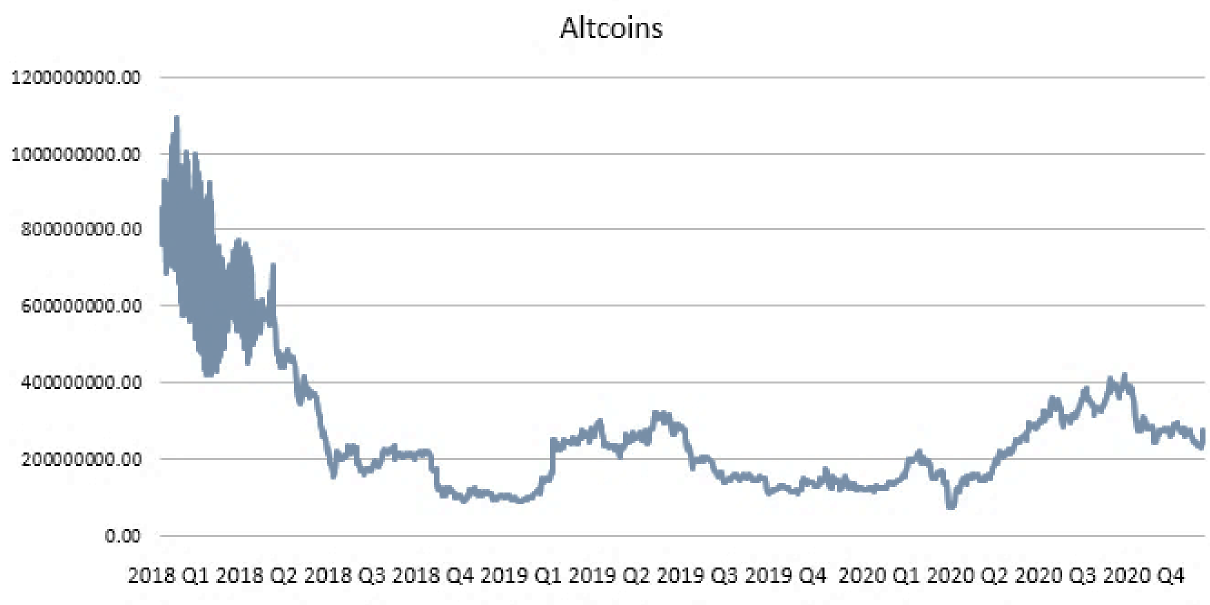

Figure 8. Market capitalization of 10 altcoins in period 2018 Q1 to 2020 Q4

Source: Prepared by an Author according to data from coinmarketcap.com

Amount of market capitalizations also highly fluctuates, which imparts that shocks in altcoin market are persistent as well. Moreover, as can be seen from the graphs, all components of the research follows similar patterns. This might indicate that Bitcoin, Ether and altcoin markets are interrelated. The effect might be mutual; however, further statistical tests are applied to check these assumptions and real effects.

Before concluding the model, statistical test of data suitability are performed. First of all, stationarity of variables is verified by Augmented Dickey-Fuller test. Table 17 below shows that none of the variables has a unit root sine ADF value is higher than critical values of 5% and 10%, therefore null hypotheses were rejected. ADF for Y is -33.317, which is higher than -2.864 and -2.568 (stationary at the level); ADL for BTC is which is also higher than -2.864 and -2.568 (stationary at 1^{st} difference); ADL for ETH is -20.857 above -2.864 and -2.568 (stationary at 1^{st} difference).

Table 17

Augmented Dickey-Fuller Test of Y, BTC. ETH

Augmented Dickey-Fuller Test			
		T-Statistic	Prob.*
ADF statistic (Y)		-33.317	0.0000
Test critical values	1% level	-3.437	
	5% level	-2.864	
	10% level	-2.568	
ADF statistic D(BTC)		-33.789	0.0000
Test critical values:	1% level	-3.437	
	5% level	-2.864	
	10% level	-2.568	
ADF statistics D(ETH)		-20.857	0.0000
Test critical values	1% level	-3.437	
	5% level	-2.864	
	10% level	-2.568	

Source: Prepared by an Author Using Eviews

Moreover, stationarity showed that the mean of time series is constant and there is no seasonality. As it is very important that variables are stationary in all VAR models, ADF Fisher Chi –Square test was also applied. The Table 18 below provides that model has p value <0.05, which again means that data used in the model is stationary and suitable for VAR.

Table 18

Stationarity Test

Stationarity Test		
Eigenvalue	Trace Statistic	Probability
ADF Fisher Chi-square	151.315	0.0000
ADF – Choi Z-stat	-7.35851	0.0000

Source: Prepared by an Author Using Eviews

Moreover, stationarity of the variables is presented in graphs (Figure 9), data is stationary at level is for Y growth rates, and data stationary at 1st difference are for BTC and ETH weekly average prices. Graphs indicates linear pattern and no seasonality, which is one of the main requirements in order to prepare Vector autoregression model.

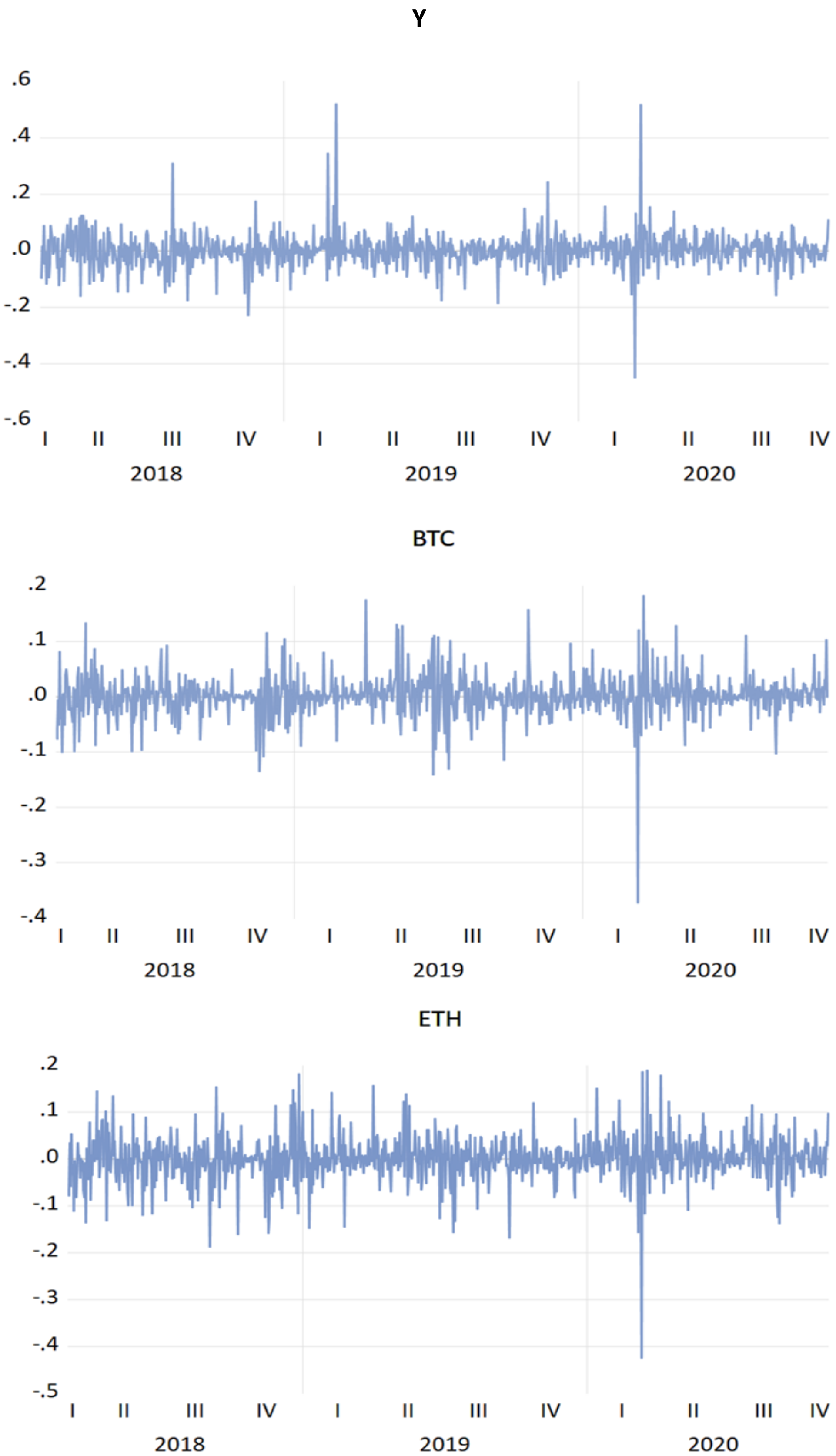

Figure 9. Data Stationarity Graph: BTC (Bticoin weekly average price), ETH (Bticoin weekly average price), Y (Post-ICO Weekly Growth Rates)

Source: Prepared by an Author using Eviews

Furthermore, the appropriate lags for VAR were chosen by using Schwarz (SC) criterion (-2.703), because it had lower value than Akaike (AIC) criterion (2.829) in the standard VAR output. In the Table 19, SC criterion indicates that the appropriate lag for SVAR is two (SC value -11.751). Therefore, for further estimations two lags are used. In addition, too many lags can lead to the loss of degree of freedom.

Table 19

Lag Selection According to Schwarz (SC) criterion

Lag Order Selected by the Criterion					
Lag	LogL	LR	AIC	SC	HQ
0.000	5687.934	NA	-11.746	-11.731	-11.739*
1.000	5699.588	23.211	-11.751	-11.741	-11.728
2.000	5706.084	12.898	-11.761	**-11.751***	-11.706
3.000	5714.091	15.847	-11.771*	-11.623	-11.686
4.000	5722.388	16.372	-11.743	-11.546	-11.668
5.000	5731.563	18.04737*	-11.743	-11.501	-11.651
6.000	5736.550	9.777	-11.735	-11.448	-11.625
7.000	5743.035	12.675	-11.729	-11.397	-11.603
8.000	5744.927	3.686	-11.715	-11.337	-11.571

Source: Prepared by an Author Using Eviews

The Granger causality test is a statistical measure that is used to determine if one variable (time series) in the model is useful to forecast other variable (time series). The results of the Granger causality test found clear relationship between some model variables. The Table 20 shows the summary statistics for Granger causality.

As a result, in this research altcoin market (Y) does not lead neither Bitcoin nor Ether markets, as probability (Prob.) is not statistically significant (null hypothesis confirmed). However, Bitcoin and Ether leads altcoin market since probability (Prob.) is lower than 0.05 (null hypothesis is rejected).The results of Granger causality test show that statistically significant relationship exists and dataset is suitable for Vector autoregression model.

Table 20

Granger Causality Test

Granger Causality Test			
Null Hypothesis	Obs	F-Statistic	Probability
BTC does not Granger Cause ETH	138	2.51218	0.0816
ETH does not Granger Cause BTC		0.57268	0.5642
Ydoes not Granger Cause ETH	138	0.04657	0.9545
ETH does not Granger Cause ALT		3.51561	**0.0301**
Ydoes not Granger Cause BTC	138	0.05063	0.9506
BTC does not Granger Cause ALT		3.87016	**0.0212**

Source: Prepared by an Author Using Eviews

Moreover, cointegration test also showed statistically significant results. *Table 20*Table 21 indicates that probability is <0.05. Cointegration test was initiated to identify if long – term relationships exist between variables. In other words, cointegreation identifies the degree to which variables are sensitive and it shows if the distance between variables persist the same.

Table 21

Cointegration test

Cointegration Test			
Eigenvalue	Trace Statistic	Critical Value	Probability
0.154982	172.6425	29.79707	0.0000
0.014362	18.72727	15.49471	0.0157
0.006005	5.505374	3.841465	0.0190

Source: Prepared by an Author Using Eviews

Null hypothesis is rejected, which established that long-term relation between variables exist and variables do not digress far from each other over the selected period of time. After main tests of VAR model was prepared, and null hypotheses were rejected of all tests, structural VAR model can be calculated and Impulse Response Function can be concluded. Therefore, further estimates were interpreted in section 3.2.2. Impulse Response Function was prepared as additional measure for more explicit result examination.

3.2.2 Interim Result Consideration of ICO Post-ICO Market Analysis

The second research model uncovered if post-ICO market is highly affected by the Bitcoin and Ether markets. When estimating equations of VAR, Durbin-Watson statistics for all equations is around 2.0 which specified that model is appropriate and can be interpreted. However, not all coefficients were significant in the model. Impulse Response Function summarized the findings and contributions of structural VAR model. Figure 10 shows how shocks to BTC and ETH causes increases and decreases in Y (the post-ICO growth rate) in predetermined length of periods (10 periods: 1 period = 2 weeks (because 2 lags were used)). Dash lines identify 95 % of confidence zone. The Impulse Response Function is prepared in the order, where (1) weekly post-ICO market growth entered first; (2) BTC average weekly closing price entered the second in the model; (3) ETH average weekly closing price entered the third in the model. This order is selected because of the assumption that Yresponds to the shocks of by BTC and ETH and not vice versa. Bitcoin and especially Ether are closely related with major part of other coins in the market: (1) usually ICOs accept payments with Bitcoin or/and Ether); (2) Ethereum is the most used technology for other token issues.

The graph in Figure 10 exhibits impulse responses to pure shocks in post-ICO market growth rates when shocks appear in Bitcoin market. X-axis indicates the time horizon, which was selected as the most appropriate for result interpretation by implementing some statistical tests in previous steps. Thereby, it reflects the 10 weeks. As can be seen from the graph, a one std. deviation shock to BTC causes increase in Y from 2nd to 4th periods (the length of period is 2 weeks). From the 5th period, Y gradually decreases below 0 and in 7th period Y significantly increases after which the effect disperse above 0 (which is expected in stationary Vector

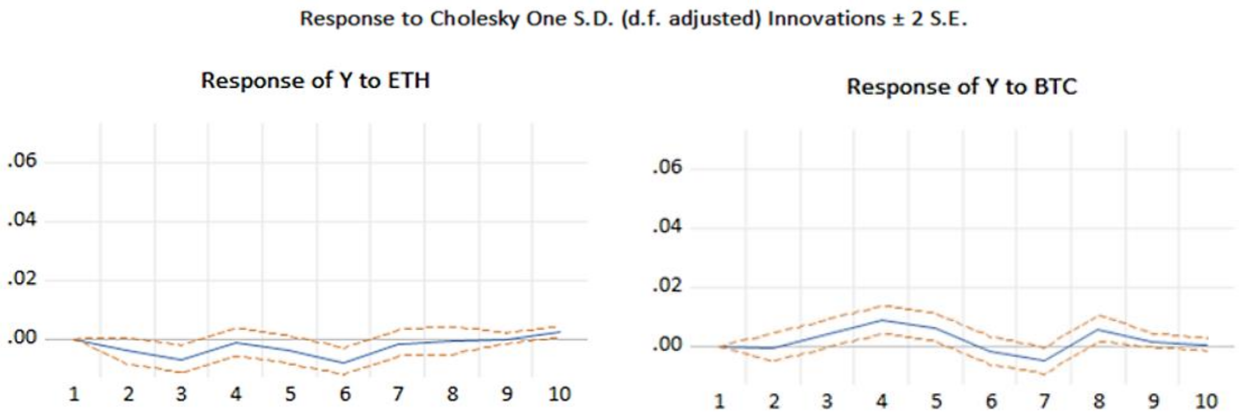

Figure 10. Impulse Response Functions: (1) Post-ICO market growth; (2) BTC av. weekly price; (3) ETH av. weekly price. Response of Y

Source: Prepared by an Author Using Eviews autoregression models). A one std. deviation shock to ETH causes decrease in Y after 1 period by declining below 0. After 3 periods, Y increases and in 4th period decreases again. After 6th period Y constantly increases and disperse above 0.

As it was assumed, shocks are meaningful for post-ICO market growth volumes, which are influenced by shocks appearing in Bitcoin and Ether markets. However, the post-ICO market growth rates do not have statistically significant influence for Bitcoin and Ether markets (Figure 11). This outcome was also explored when initiating Granger causality test.

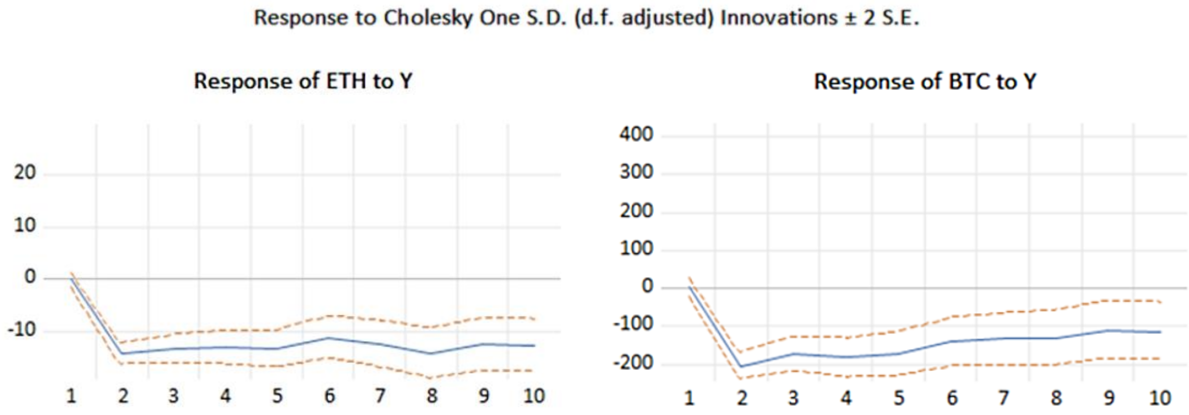

Figure 11. Impulse Response Functions: (1) Post-ICO Market Growth; (2) BTC Daily Close Price; (3) ETH Daily Close Price. Response to Y

Source: Prepared by an Author Using Eviews

The second model of the research revealed that post-ICO market is affected by the shocks occurring in Bitcoin and Ether markets. As a result, Impulse response Function tracks the effects of structural shocks of the endogenous variables included in the model during the predetermined periods with lag of 2. The responses to Bitcoin market as well as to Ether market is not persistence.

3.3 Discussion and Outlook of ICO Crowdfunding and Post-ICO Market Analysis

The analysis aspired to investigate which elements have the most influence on ICO gains in crowdfunding stage and to examine post-ICO token market performance. Thereby, this inquiry was designed based on main aim that was formed and problems that were raised by analyzing recent literature. One of the most important aspirations in this research was to examine not only one small part of ICO process but include wider prospect thus involving post-ICO market analysis. Since 2017 the post-ICO market is gradually increasing and that makes it very important part of ICO mechanism. As a result, both research models indicated statistically significant results.

The first econometric model disclosed that the amount raised during the ICO is not as highly affected by the availability of a white paper as by open source code availability. Investors might not value white paper as it does not have any certification and requirements how it should be composed as well as it is not audited. In the event of that transparency and the quality of information is not ensured, white paper is a medium for spurious interpretations and falsification. While published code is considered as a proof of campaigns trustworthiness. Pre-sale also does not have significant affection (only the modest) in this analysis, however, some other researchers (e.g. Adhami et al., 2018) have identified pre-sales as highly and positively important for ICO early funding. Adhami et al. (2018) argued that higher gains of ICO are affected by the ability to attract success primary market interest. However, pre sales are risky because of the uncertainty of future project; therefore, they might not attract as many funds as expected. Nevertheless, pre-sales can help to prepare and inform market about the particular ICO and its idea, aims, structure and completeness, which lead to the higher gains during the main stage but relationship is not direct. Some other authors also indicated that bonus schemes might affect ICO profitability but only fractionally. Moreover, according to this research, predetermined investment goal of the ICO is positively related to increased gains in ICO. Although, this was not acknowledge in recent researches towards ICO as highly influential aspect. Usually, hard caps help participants to foresee the blockchain-based token sales potential and aspirations.

Moreover, many other aspects must be taken into consideration as well while analyzing ICOs. For example, idea of the project, market condition, timing, team qualification, quality of disclosure channels, etc. One of the main aspects while ICOs fail is that while developing blockhain-based projects, founders sometimes lack of understanding of the economic part and dimension of creating long lasting projects. In addition, ICOs faces many risks, such as hacker attacks due to security flaw, spuriously recognized as a fraud by the online community, etc.

Post-ICO market analysis indicated that shocks of Bitcoin and Ether market induces altcoin market. Major part of ICOs in the market are based on Ethereum blochchain and influence of Bitcoin usually arise because altcoins are measured in Bitcoin. Yet there is lack of literature regarding to secondary market, but some recent studies (Masiak et al., 2019) have identified as well that post-ICO market is highly influenced. However, they have indicated that shocks appear in up to eight weeks after the impact, while model with most successful projects revealed that effects occur from 4th to 8th week.

As both analysis models provided with the statistically significant findings, further investigations in relation to ICO crowdfunding stage and post-ICO market can be produced. First of all, the same analysis can be employed by differentiating ICO projects geographically or by recognizing investors by diverse countries profiles (as the appetite for risk tolerance and aims can highly differ). Moreover, blockchain-based token sales crowdfunding analysis can be divided into specific fields. For instance, separate analysis of marketing strategies (e,g. bonus schemes, pre-sales, and early birds) or ICO characteristics that relates to the design of the campaign, might provide further and more peculiar insights about specific direction. Secondly, post-ICO market performance can be conducted by applying different parameters when selecting the appropriate projects for the analysis thus expanding the time horizon and by applying different lags in VAR.

Furthermore, ICOs brought many interesting questions/problems for academics. In 2020, the most analyzed topics concerning ICOs were towards token market returns, market efficiency and disclosed information asymmetry. Since new implications of regulation in ICO markets contributed to ICO volumes decline, problems such as what would help companies to reduce risk for investors in partially regulated markets and what would help projects to surface are relevant to explore.

To summarize, this twofold investigation was designed to explore ICO process including ICO crowdfunding stage as well as post-ICO market analysis. The third part concludes that key factors that influences higher funds raised in ICO crowdfunding stage are proof of code available for public and predetermined hard cap and that post-ICO market is affected by two most prevailed cryptocurrencies – Bitcoin and Ether. Generally, these findings are consistent with other researches that were already introduced in the scientific literature; however, some new insights were discovered. Despite the limitations that were face while constructing research models, received findings were reliable and demonstrated statistically significant effects.

CONCLUSIONS AND RECOMMENDATIONS

An amount of empirical researches towards ICO economy is rapidly evolving. According to the literature, the emergence of Initial Coin Offerings has brought many new opportunities for business but also implied not a few threats for participants. Companies at the early stage are provided with the new way of funding, which can be considered as an alternative for conventional funding approaches (Venture capitalists, Angel investors, crowdfunding, etc.). However, unlike standard funding methods, ICO gives possibility for intermediation, anonymity, and helps to remove geographical boundaries. Moreover, ICO mechanism is fully automated (from initial stage to post-ICO stage). Token sales are blockchain-based and are built by using smart contracts. In addition, ICO gives the opportunity to create own company's network even before producing the actual product by issuing different types of tokens (utility, currency, equity, etc.). Major part of ICOs provide secondary market trading possibility. Because of this latter opportunity, ICOs are mainly compare to IPOs. However, there are many substantial differences and the main one is that during the ICO investors do not buy the underlying asset; they buy the money supply of the future's project. Besides, ICO investors are more risk seeking than, for instance, IPO investors. The primary difference between investors' profiles are their aim of investment. Some literature investigated that technological motives are ones of the most important to ICO investors compared to other causes due to confident in blockchain technology and its potentials. In addition, investors are engaged by the anonymity and decentralization.

However, there is lack of clear and continious regulations in ICO market. No restrictions and supervision are applied for information that should be disclosed to participants. Literature emphasized that this situation might lead to counterfeiting of the project and its potential in order to collect vast amounts money. Therefore, recent literature imparted that high information asymmetry exists in blockchain-based token market and it lacks of transparency. The latter situation occurs because investors are unable to identify spurious information that might be delivered to ICO participants. Each investor may understand and interpret information differently due to the diverse disclosure channels. Nevertheless, individuals are getting more and more aware of reliable ICO signals, and participants usually are perspective customers and trustworthy campaigns. In addition, in some countries ICO are prevailed more than in other. Several researches revealed that countries with clearer legal and regulatory framework towards ICOs are more valued by participants than countries without any regulations applied.

After analysis of diverse researches' findings, methods and variables used in the recent academic literature, two researcher models were constructed. Weighted Least Square Multiple Linear regression was chosen to examine ICO crowdfunding stage, as it is the most suitable for heteroscedastic data. Vector Autoregression (VAR) was used for post-ICO market performance inquiry as it helps to analyze pure shocks in the markets.

The twofold model of this research revealed what determinants influences ICO profitability the most in crowdfunding stage and how post-ICO market is affected by Bitcoin and Ether markets. Firstly, WLS regression analysis examined which aspects influences higher ICO gains. This research model uncovered that key factors are open source code availability and preset hard cap. The econometric analysis discloses that total funds raised in ICO crowdfunding stage are not affected by the availability of a white paper. Participants do not value white paper as it does not have any certification and it is not supervised, which may lead to falsification. On the contrary, the set of blockchain codes, which is publicly accessible, is highly valued by ICO participants. Even the availability of partial set of code is as proof-of-concept of ICO project's reliability. Nevertheless, code availability is more valued by the professional cryptocurrency market investors; non-professionals mostly rely on white paper. The second key factor revealed by the first research model is hard cap. ICO contributors tend to invest more in those projects that has predetermined maximum goal of investment. It helps investors to measure and foresee the ICO success. On the contrary, based on research results, soft cap does not influence investors' favor to one or another ICO project. Moreover, first part of the analysis disclosed that in this particular model the type of token (as major part of tokens are utility), type of blockchain, the acceptance of both currency (cryptocurrency and fiat), and minimum contribution do not have effect on total funds raised. Research also indicated that predetermined total supply does not influence ICO profitability. Although, larger part of supply available for public than for private investors has a marginal importance. Furthermore, bonus scheme is used as a marketing tool in order to attract contributors. Since there are many different bonus schemes, their effect should be examined separately. In the pool together with other elements, bonus schemes do not have statistically significant impact. Pre-sales also do not have significant affection (only modest) in this analysis. However, some researchers (e.g. Adhami et al., 2018) have identified that pre-sales are positively important for ICO early funding. However, many other aspects must be taken into consideration as well while analyzing ICOs. For example, idea of the project, market condition, timing, team qualification, quality of disclosure channels, etc.

Secondly, VAR model explored the performance of listed tokens in post-ICO market. ICO projects for this model were selected with specialties that were explored highly important for ICO profitability. The second research model uncovered that post-ICO market is highly affected by the Bitcoin and Ether prices. Analysis indicated that shocks to Bitcoin and Ether markets causes increases/decreases in post-ICO market (particularly ICO growth rates). Pure shocks were discovered in post-ICO market when shocks appear in Bitcoin and Ether markets. One standard deviation shock to Bitcoin market causes increase in post-ICO market from 4^{th} to 8^{th} weeks. From the 10^{th} week, post-ICO market growth rates gradually decreases below 0 and around 14^{th} week post-ICO market growth rates increases again after which the effect disperse above zero. A one standard deviation shock to Ether causes decrease in in post-ICO market after 2 weeks by declining below 0. After 6 weeks post-ICO market growth rates increases and around 8^{th} week decreases again. After 12 weeks post-ICO market constantly increases and disperse above zero. Shocks are meaningful to post-ICO market growth rates; however, the post-ICO market influence for Bitcoin and Ether markets was not discovered in this particular research.

To finalize, ICOs have prevailed very quickly by bringing new way of financing to early stage companies. The 2017 was the most prosperous year for ICO market. However, in the mid-2019, ICO volumes started to decrease. This decline most likely occurred because of the regulations that policy-makers started to undertake and uncertainty of future restrictions. The minimum investment requirement was imposed, which has forced out small investors slowed down ICO processes. However, already initiated projects have demonstrated that they have created strong lasting businesses. Therefore, ICOs might help to improve cryptocurrency market further as the prevalence of ICO brought many benefits to businesses. This phenomenon has a potential to change the way of funding for companies by reducing intermediation, providing secondary market liquidity, less costs and more control for initiators. Nevertheless, it will take a lot of time to adopt new technologies in order to replace or improve existing conventional infrastructures.

Recommendations. Referring to the limitations of this research, there is no aggregate database for all ICO projects with continuous information. For the researchers, before compiling dataset, the data needed for the research should be carefully defined, and, as a first step, reliable dataset with the highest availability of required information found. Furthermore, this study provides that initiators should give very explicit information to the market in order to attract higher gains. According to this analysis, information that investors are willing to receive is predetermined maximum goal as well as open source code disclosure. Therefore, this study might help to recognize what affects ICO profitability in crowdfunding stage and what aspects should be more considered before establishing ICO. Moreover, this research also revealed considerable information to investors. It helps to identify what features of ICO are highly influential and the most valued in the market between participants. Thereby, it helps to sort out the projects with higher potentials. In addition, investigation towards post-ICO market imparts relevant insights for traders regarding altcoin market relation with Bitcoin and Ether.

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BLOCKCHAIN-BASED TOKEN ECONOMY: ICO CROWDFUNDING AND POST-ICO MARKET PERFORMANCE

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SUMMARY IN LITHUANIAN

62 psl., 21 lentelė, 11 pav., 58 šaltiniai.

Pagrindinis baigiamojo darbo tikslas yra išanalizuoti faktorius, lemiančius didesnę surinktų lėšų sumą pirminio viešojo kriptovaliutų siūlymo sutelktinio finansavimo etape, ir ištirti žetonų antrinę rinką. Baigiamasis darbas susideda iš trijų pagrindinių dalių. Literatūros analizėje nagrinėjama blokų grandinės pagrindu veikianti žetonų ekonomika, mokslinių darbų tyrimų metodai bei gauti rezultatai. Metodologijos dalis apima dviejų kiekybinių tyrimo modelių formavimą. Praktinėje dalyje analizuojami pirmojo ir antrojo empirinių tyrimų rezultatai.

Atlikus literatūros analizę, buvo pasirinkti du statistiniai modeliai baigiamojo darbo tyrimui įvykdyti. Pirmuoju modeliu (svertine mažiausių kvadratų regresija) išanalizuota, kokie veiksniai lemia viešojo kriptovaliutų siūlymo pelningumą pirminio sutelktinio finansavimo etape. Projekte surinktų lėšų suma buvo pasirinkta kaip priklausomas tyrimo kintamasis, nepriklausomi kintamieji buvo suskirstyti į tris pagrindines kategorijas: finansiniai aspektai, techniniai aspektai ir kriptovaliutų siūlymo charakteristikos. Antruoju modeliu (vektorine regresija) išnagrinėta, ar antrinę žetonų rinką paveikia "Bitcoin" ir "Ether" rinkose atsirandantys struktūriniai šokai. Šį modelį sudaro trys kintamieji: vidutinė "Bitcoin" ir "Ether" savaitės kaina bei antrinės rinkos augimo koeficientas, sudarytas iš projektų, atrinktų remiantis pirmuoju tyrimu). Analizė parengta naudojant „R“, „Eviews“ ir „SPSS“ programines įrangas.

Pirmasis tyrimo modelis atskleidė, jog finansiniai ir technologiniai aspektai daro įtaką surinktai lėšų sumai. Antrasis tyrimo modelis nustatė, kad "Bitcoin" ir "Ether" rinkos paveikia antrinę žetonų rinką, tačiau atvirkštinis ryšys nebuvo rastas. Išvadose ir pasiūlymuose apibendrinta literatūros analizė ir dviejų tyrimų rezultatai.

Baigiamojo darbo tyrimo rezultatai buvo pristatyti „World Finance & Banking Symposium” konferencijoje, vykusioje 2020 gruodžio 5-6 d. ir yra pateikti publikavimui „Economic and Business Rieview“ moksliniame žurnale.

ANNEXES

Annex 1. Weighted Least Squares Regression: Correlation Matrix (prepared by an author: R software output)

KENDALL TAU CORRELATION														
VARIABLES	T_FUND_RAISED	WHITE_AV	OPS_COD_AV	T_SUPPLY	PUB_SUPPLY_PERC	OWN_BLOCK	ICO_DUR	TYPE_TOKEN	BON_SCH	PRE_SALE	BOTH_CUR_ACC	HARD_CAP	SOFT_CAP	MIN_CONTR
T_FUND_RAISED	1.000	-0.047	0.370	0.132	-0.178	0.016	0.061	0.093	-0.076	0.110	0.170	0.419	0.116	0.079
WHITE_AV	-0.047	1.000	0.003	-0.010	0.006	0.037	0.114	-0.058	-0.077	0.048	-0.058	0.083	0.035	-0.004
OPS_COD_AV	0.370	0.003	1.000	-0.040	0.142	-0.090	0.027	-0.034	0.161	-0.038	0.041	-0.015	0.106	-0.156
T_SUPPLY	0.132	-0.010	-0.040	1.000	-0.108	0.012	-0.025	-0.033	-0.049	0.042	-0.016	-0.013	-0.059	0.033
PUB_SUPPLY_PERC	-0.178	0.006	0.142	-0.108	1.000	-0.026	-0.022	-0.106	0.126	-0.155	0.062	-0.037	-0.027	-0.175
OWN_BLOCK	0.016	0.037	-0.090	0.012	-0.026	1.000	0.087	-0.080	-0.092	-0.050	-0.045	0.055	-0.089	0.195
ICO_DUR	0.061	0.114	0.027	-0.025	-0.022	0.087	1.000	-0.080	-0.079	0.073	-0.042	0.024	0.027	-0.217
TYPE_TOKEN	0.093	-0.058	-0.034	-0.033	-0.106	-0.080	-0.080	1.000	-0.077	0.021	0.036	0.063	0.085	-0.017
BON_SCH	-0.076	-0.077	0.161	-0.049	0.126	-0.092	-0.079	-0.077	1.000	0.202	0.135	0.036	0.132	-0.094
PRE_SALE	0.110	0.048	-0.038	0.042	-0.155	-0.050	0.073	0.021	0.202	1.000	0.097	0.118	0.166	0.005
BOTH_CUR_ACC	0.170	-0.058	0.041	-0.016	0.062	-0.045	-0.042	0.036	0.135	0.097	1.000	0.207	-0.022	0.037
HARD_CAP	0.419	0.083	-0.015	-0.013	-0.037	0.055	0.024	0.063	0.036	0.118	0.207	1.000	0.203	0.087
SOFT_CAP	0.116	0.035	0.106	-0.059	-0.027	-0.089	0.027	0.085	0.132	0.166	-0.022	0.203	1.000	-0.089
MIN_CONTR	0.079	-0.004	-0.156	0.033	-0.175	0.195	-0.217	-0.017	-0.094	0.005	0.037	0.087	-0.089	1.000
N of all variables	201	201	201	201	201	201	201	201	201	201	201	201	201	201