SCHOOL OF ECONOMICS AND MANAGEMENT

The Impact of the Founding Team's Human Capital on Token Sale Success

An analysis of European ICOs between 2016-2021

ENTN19 - Degree Project in New Venture Creation

Master of Sciences in Entrepreneurship and Innovation

Authors: **Amrit Gill** & **Geoffroy Leuba**

Supervisor: **Andrea Moro**

Examiner: **Zahida Sarwary**

Final Seminar: May 25th, 2022

Abstract

The emergence of blockchain technology enables entrepreneurs to raise capital in an innovative way, by addressing a crowd of online investors without the need for an intermediary. This phenomenon is known as token sales, and it may have the potential to revolutionize entrepreneurial finance. However, information asymmetry is particularly severe in this context, and the need for entrepreneurs to send signals to investors arises as an essential challenge to venture financing. We explore the possible impact that human capital may play as a signal for initial coin offerings (ICOs), a type of token sale. By looking at the education of the entrepreneurial team, as well as the relevant skills of its members, our findings suggest that human capital does not play a significant role in ICO success. Interestingly, we found that the number of Twitter followers is significant in relation to ICO success. We believe that herd behavior and a lack of due diligence may explain these results. We open the discussion for further investigation.

Key words: entrepreneurship, entrepreneurial finance, token sales, initial coin offerings, ICO, information asymmetry, signaling theory, human capital.

Acknowledgements

The authors of this study want to express their gratitude towards Prof. Dr. Andrea Moro for his support, guidance, and feedback through the process of research and writing this thesis.

Table of Contents

1. Introduction 4

2. Theoretical Framework 7
    2.1. Token Sales: A Disruptive Venture Financing Tool 7
        2.1.1. Blockchain Technology 7
        2.1.2. A Revolution for Entrepreneurial Finance 8
        2.1.3. Investment Factors in TS 10
    2.2. The Role of Human Capital in Traditional Financing 11
        2.2.1. Influence of Human Capital on Venture Financing 11
        2.2.2. Information Asymmetries & Signaling Theory 14
    2.3. Breakdown of Human Capital From an Entrepreneurial Perspective 15
        2.3.1. General and Specific Human Capital 15
        2.3.3. Role of Human Capital in Token Sales 16

3. Methodology 17
    3.1. Research Design 17
    3.2. Data Collection 17
    3.3. Sample 18
    3.4. Operational Definitions and Measures 18
    3.5. Data Analysis 20
    3.6. Descriptive Statistics & Statistical Tests 21

4. Results 23
    4.1. Control Variables 23
    4.2. Model I 25
    4.3. Model II 26
    4.4. Model III 27
    4.5. Analysis of Extreme Quartiles 28
        4.5.1. Lower Quartile Analysis 28
        4.5.2. Upper Quartile Analysis 30

5. Discussion 32
    5.1. Potential Explanations of Results 32
    5.2. Limitations 34
        5.2.1. Methodological Limitations 35
        5.2.2. Data Limitations 36
    5.3. Further Research 37

6. Conclusion 39

References 41

1. Introduction

The emergence of cryptocurrencies, and its underlying blockchain technology, disrupts current financial institutions; some scholars interpret them as a revolution for the financial world (Chen, 2018; Fisch, Meoli & Vismara, 2020). Tapscott and Tapscott (2016) see these technological developments as potential upheaval for the business world in the coming years. Although blockchain and cryptocurrencies disrupt the financial world, an underarching phenomenon has attracted attention in the entrepreneurial finance domain: token sales (Fisch, 2019; Kranz, Nagel & Yoo, 2019).

Token sales (TS) are a novel venture financing mechanism that consists of selling digital tokens to a crowd of online investors using a decentralized system of transactions (Kranz, Nagel & Yoo, 2019). Start-ups can raise capital directly from investors who invest in cryptocurrency markets. Although this may revolutionize entrepreneurial finance, the lack of regulations concerning this highly innovative financing method, coupled with the technical aspects, leads to severe information asymmetry (Chen, 2019; Chen & Chen, 2020; Fisch, 2019; Fisch, Meoli & Vismara, 2020). In this context, signals that entrepreneurs send to investors in order to diminish information asymmetry come as critical assets to secure financial resources. Some of these signals that founders can send to stakeholders are their knowledge, education, skills, experiences, or in other words, their human capital (Ante, Sandler & Fiedler, 2018). TS have attracted the attention of scholars who have studied key factors that impact token sales success, as well as signals sent by founders (Chen & Chen, 2020). However, research on the influence of human capital of the founding team on TS success remains underexplored.

This study intends to examine a potential relationship between the human capital of the founding team and the success of token sales. For the sake of this study, 'founding team' refers to the CEO, CTO and CFO, as this was the information available on the database used in this research. We conduct exploratory research using a quantitative method to analyze more than 1,000 European Initial Coin Offerings (ICOs), which is a type of token sales, through the lens of the founding team's human capital. We aim to provide an answer to the following research question:

Does the human capital of the founding team have an impact on token sale success?

The present study proceeds as follows. The next part provides a theoretical framework for our research (2). The first section (2.1) presents token sales, a novel venture financing mechanism that makes use of the latest technological developments, specifically with regard to blockchain technology. We introduce the concept of blockchain (2.1.1) as an underlying technology of TS. We also present the disruptive nature of TS (2.1.2) and use literature to present key factors that affect the dynamics of this novel type of venture financing (2.1.3).

Thereafter follows an analysis of the role that human capital plays in traditional financing methods (2.2). We present the extent to which human capital impacts financing using relevant literature (2.2.1) and describes this relationship using the concept of information asymmetry and signaling theory (2.2.2). In the next section (2.3), we divide human capital into two dimensions to frame our research: general and specific (2.3.1). The theoretical framework ends with a brief overview of the notion of human capital in the TS context.

After this, we present our methodology (3), which includes the research design (3.1), data collection (3.2), the construction of our sample (3.3), the presentation of operational definitions and measures (3.4), an explanation of the data analysis (3.5), and lastly we conduct descriptive statistics as well as several statistical tests (3.6).

Then we present our findings in section (4), which states that human capital does not seem to have a significant impact on TS success. First, we select control variables that have proven to affect ICO success (4.1). General human capital, measured by the total number of years of higher education of the CEO, CTO, and CFO, does not have a significant impact on ICO success (4.2). The specific human capital of the same members of the founding team, as measured by the skills relevant to the ICO's industry, also does not have a significant impact on ICO success (4.3). Overall, human capital does not have a significant influence on ICO success (4.4). However, we found that Twitter followers and team size do affect ICO success. Based on those observations, we delve into the upper and lower quartiles in terms of Twitter followers of the dataset (4.5) and found that human capital seems to have a more significant impact in ICOs with fewer followers.

We attempt to examine the potential causes of this phenomenon in the discussion section (5.1). We investigate both herd behavior and the lack of due diligence from investors as possible elucidation of our findings. In the same section, we present the limitations of our study (5.2) and open up considerations for further research (5.3).

We conclude by explaining the contribution of our work to the TS domain and present the potential implications for entrepreneurs, investors, legislators, and academics (6).

2. Theoretical Framework

Access to finance has proven to be a crucial aspect of entrepreneurship, especially when it comes to firm survival and success. Indeed, the existing literature about entrepreneurship suggests that financing constitutes one of the most challenging aspects of venture creation and development for entrepreneurs (Kerr & Nanda, 2009). Kim and Hann (2019) also emphasize the importance for entrepreneurs to have a strategic approach when attempting to secure sufficient financial resources. They found in their study that a significant majority of entrepreneurs suffer from a lack of capital. Other studies suggest that the initial capital a venture is able to secure in its early stages has a significant impact on the success of the firm, with undercapitalization reasoned to be a “major cause of small business failure” (Headd, 2003; Van Auken & Carter, 1989, p. 1). In fact, most small-to-medium enterprises in Europe don’t tend to survive beyond the three year mark (Vasilescu, 2019). Lastly, access to financing fosters entrepreneurship and growth (Cole, Cumming & Li, 2016). Undoubtedly, the importance of the ability to raise capital at founding is well-accepted by scholars.

Our theoretical framework is constructed as follows. Firstly, we provide an overview of token sales as a novel financing mechanism. Secondly, we explore the role that human capital plays in traditional financing. This section builds on signaling theory as a means to reduce information asymmetries between entrepreneurs and investors. Thirdly, we conclude by breaking down the concept of human capital in general and specific dimensions and design the framework we are using for our methodology.

2.1. Token Sales: A Disruptive Venture Financing Tool

2.1.1. Blockchain Technology

The emergence of decentralized ledger technology (DLT) revolutionized the way transactions can be recorded (McLean & Deane-Johns, 2016). DLT consists in spreading the record of any data or transactions (in a commonly shared ledger) among many different computers that follow one unique protocol in a peer-to-peer (P2P) network. The protocol represents the way data is recorded and shared in the P2P network. The most famous protocol known to this day is the Bitcoin protocol, a cryptocurrency that relies on blockchain technology.

Blockchain technology is a particular type of DLT, perhaps the most used one due to its wide number of applications, one of them being cryptocurrencies. Simply put, blockchain technology is a consensus in which transactions are recorded in blocks of information linked to each other, forming a chain, hence the name blockchain (Natarajan, Krause & Gradstein 2017). In other words, blockchain is a new way of structuring data recording and sharing. These blocks, which are shared among a P2P network, are verified by miners who complete hash functions in order to verify the legitimacy of the transaction (preventing double-spending, etc.). Once a block has been verified by a miner, the P2P network validates the work of miners and the block is linked to previous blocks.

Intrinsic features, such as transparency, immutability, irreversibility, and verifiability (Chen, 2018; Kranz, Nagel & Yoo, 2019) make it a powerful technology for applications in finance, in particular. Recognizing the power of such features, developers created cryptocurrencies using this technology. As a consequence, blockchain (and more generally decentralized ledgers) constitute the underlying technologies behind cryptocurrencies. Cryptocurrencies represent revolutionary digital monetary systems that do not require a central entity for regulation (Hossain, 2021). The use of cryptography for security gave the name to these virtual currencies: namely, cryptocurrencies. Taking all this into consideration, this technological development presents a disintermediating ecosystem for entrepreneurial finance.

2.1.2. A Revolution for Entrepreneurial Finance

While the introduction of these technologies and their applications revolutionized financial markets, TS made use of these technologies by providing a disruptive tool for entrepreneurs to raise capital. Token sales should be understood as a mechanism through which an issuing entity (such as a founding team of entrepreneurs) creates and sells digital, cryptographic tokens to a crowd of online investors in order to raise capital for a project. The digital tokens can take many forms and endorse different purposes and can represent any scarce assets. Kranz, Nagel & Yoo (2019) identify four types of tokens. First, *utility tokens* represent the most common type of tokens used to raise capital. They have a function of access or usage guarantee for their holders. Investors who buy these tokens are able to use them on the platform or application developed by the issuing entity. Second, *currency tokens* represent digital money that is built on blockchain technology, known as cryptocurrencies. Third, *donation tokens* are sold to investors who want to support the development of a project. These are particularly relevant for idealistic projects that convey a vision that many people share. Finally, the fourth type is *security tokens*, which are comparable to stock shares as they provide the holder a portion of future profits or even voting rights while being issued and recorded on a blockchain (in other words: a distributed ledger).

Once the team of developers decides which type of tokens to issue and sell, they create a “smart contract”. Smart contracts are code lines that define a set of rules for TS, such as defining the price (usually in terms of accepted cryptocurrencies) of each token, the duration of the initial sale, etc. (Florysiak & Schandlbauer, 2022). In order to share all this relevant information with the public, i.e. potential investors, entrepreneurs, and developers create a white paper (WP), which should be understood as an online document that explains relevant aspects of the project to the public, such as the business concept, team information, the function of the tokens used and any information regarding the initial TS (Samieifar & Baur, 2021). Interestingly, they are unregulated documents, which allow entrepreneurs to disclose the aspects of the project they want to the public. Hence, the whole process of raising capital does not require any intermediary as entrepreneurs are able to directly interact with many thousands of potential investors from all across the globe, propelled by this advanced technology.

This novel mechanism to raise money for start-ups includes different types of TS. The most known type of TS to this date is ICO. The goal of this study is not to make any distinction between TS types for mainly two reasons. First, although slight differences occur between different types of TS, the revolutionary, underlying mechanisms remain the same. Second, new TS types are likely to emerge in the near future, making an exhaustive list of TS types potentially obsolete.

Figure 1 below shows the whole TS ecosystem and presents all interactions between investors and the issuing entity, thus highlighting the disintermediating nature of TS and its effect on venture financing.

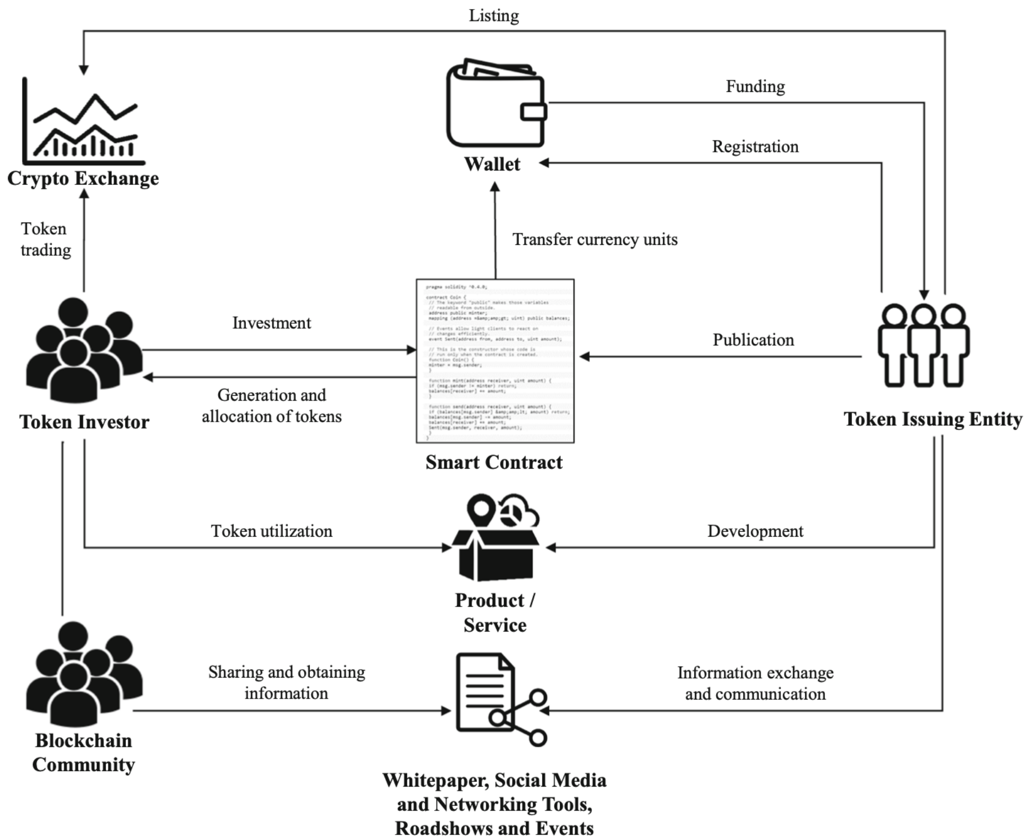


Figure 1: TS ecosystem (Kranz, Nagel & Yoo, 2019).

The process described above demonstrates to what extent TS revolutionized venture financing. By leveraging blockchain technology to raise capital among a crowd of online investors, TS removes intermediaries that are necessary for traditional fundraising mechanisms, such as VCs, BAs, banks, etc. (Kranz, Nagel & Yoo, 2019). This aspect of TS is fundamental as the market for venture capital can thus be spread among individuals, bypassing traditional constraints to invest in new ventures (Casarella & Manfrè, 2019; Chen, 2018). In other words, this changes the relationship between entrepreneurs and investors.

2.1.3. Investment Factors in TS

Given the recent phenomenon of blockchain technology and thus token sales, limited studies have been done on the role of investors in cryptocurrency-based markets. The investor sector for TS is open to the general public, and albeit limited to those with internet connection and current know-how of blockchain platforms, it remains a significantly more accessible market (Chen, 2018; Rohr & Wright, 2019). What also remains largely unexplored are the criteria that TS investors base their judgments on when it comes to investment decisions in the context of ICOs (and similar token sales). Studying these criteria may allow entrepreneurs, investors, and legislators to understand how TS can be successful, enabling start-ups to secure the financial resources necessary to pursue their projects.

Chen and Chen (2020) provide an overview of some aspects related to ICO success studied thus far in Figure 2. They build further on this topic by identifying three groups of factors that determine the success of ICOs: technological capabilities, characteristics of ICO campaigns, and characteristics of companies. To add to this growing research, we look at one factor that has been underexplored in the existing literature, which is the role of human capital. In order to start framing this analysis, we take a look at the role human capital plays in traditional financing.

Key success factors of ICO identified in the literature.

Groups	Factors	Dep. Vars.	Literature
Technical capbiities	White paper quality	Success of ICO	Moro and Wang (2019)
	Tech white paper	Funds raised	Fisch (2018)
	Hi-qual source code		
ICO campaign characteristics	Token sale	Funds raised	Felix and Eije (2019)
	Trading volume	Underpricing	
	Issuer retained ratio		
	Coins sold ratio		
	Legal jurisdiction	ICO success	Adhami et al. (2018)
	Social media use		Fisch (2019)
Company characteristics	Team size	ICO success	Fenu et al. (2018)
	Advisory size	ICO success	Giudici and Adhami (2019)
	Entrepreneur team education		
	Investors' motives	ICO investment	Fisch et al. (2019)

Figure 2: Overview of the existing research exploring the influence of success factors on ICO outcomes (Chen & Chen, 2020).

2.2. The Role of Human Capital in Traditional Financing

2.2.1. Influence of Human Capital on Venture Financing

Human capital is a set of knowledge and skills acquired by the individual that contributes to the efforts of any group or organization (Sturman, Walsh & Cheramie, 2008). In the context of entrepreneurship, human capital creates information assets that are highly valuable in the function of a venture (Becker 1964, cited in Gimmon, 2008; Smart, 1999). Human capital has played a vital role in forming new ventures (Baptista, Karaöz & Mendonça, 2014; Honjo, 2021). Research has shown multiple benefits of considering the human capital of the founding team, primarily because the prior knowledge and resources of the founding team affect opportunity recognition and resource acquisition in the early stages of the start-up

(Agarwal, Echambadi, Franco & Sarkar, 2004). Honjo (2021) supports this idea with his research and explains that start-ups that are managed by founders with a higher level of human capital tend to raise more capital than founders with lower human capital. Ko and McKelvie (2018) found that founders' human capital has an important impact on entrepreneurs' ability to raise capital through various funding stages, particularly during the early stages. Therefore, the entrepreneurs' ability to access financial capital relies heavily on their human capital. In order to understand the role that human capital has played in entrepreneurial finance, we review its role in various traditional financing methods. Additionally, we demonstrate the limits of these financing methods.

The first means of venture financing consists in the founder's personal wealth. This may be through personal savings and/or assets, or even the liquidation of a previous company (in the case of serial entrepreneurs). Alternatively, entrepreneurs can move on to friends and family who offer money either by gift or loan, hence expecting returns from their relatives at a later stage. However, these informal ways to fund a new venture are limited by the founder's personal resources both in terms of social and financial capital. Furthermore, capital-intensive projects are likely to require more funds than the so-called 3Fs (namely friends, family, and fools) are able to provide (De Clercq, Fried, Lehtonen & Sapienza, 2006; Honjo, 2021). Storey and Greene (2010) also suggest that financing a venture through these informal capital providers risks compromising the founders' and their relatives' personal wealth, thus highlighting another shortfall. Therefore, entrepreneurs may want to turn to more resourceful financing intermediaries to raise larger capital for their ventures.

Bank loans represent another way to access capital for entrepreneurs. However, banking institutions, as capital providers, tend to shy away from high-risk investments when it comes to venture financing (De Clercq et al., 2006). Furthermore, Honjo (2021) mentions that since the financial crisis of 2008, banking institutions drastically reduced their investments in new ventures, making it even harder for entrepreneurs to raise capital via these intermediaries. He goes on to say that banks also require collateral from entrepreneurs to reduce the level of risk they have to assume, which again returns to the problem of the limited resources of founders. Grilli (2019) adds to this the struggle of innovative start-ups to secure financing via banking institutions due to the high information asymmetry that applies in this context. Hence, both capital suppliers mentioned previously (informal capital providers and bank loans) seem to not fit the financial needs of high-risk, high-tech start-ups, which typically require the most funding (Honjo, 2021). These limits can be addressed with signals entrepreneurs can provide, one of which is human capital. Indeed, scholars agree that human capital plays a key role in venture financing through bank loans (Bates, 1990; Bruns, Holland, Shepherd & Wiklund, 2008; Coleman, 2004).

As a consequence, entrepreneurs can access capital via a few other traditional intermediaries such as business angels and venture capitalists, which represent the majority of early-stage investments for new ventures (Mollick & Robb, 2016). In their study, Mollick and Robb (2016) explain that business angels and venture capitalists mostly provide financing to highly educated individuals, emphasizing the importance of human capital to access financial capital via these intermediaries. MacMillan, Siegel & Narasimha (1985) also suggest that venture capitalists value the personality and experience of the entrepreneur the most when deciding to finance a venture. Similarly, venture capitalists and business angels' financing decisions are strongly correlated to the characteristics of the founders, in other words, their human capital (Grilli, 2019; Tenca, Croce & Ughetto, 2017). This is particularly the case in "knowledge intensive sectors", such as high-tech industries where human capital plays the role of the primary resource for the firm's performance (Colombo & Grilli, 2005). Overall, human capital has proven to play a major role in venture financing via business angels and venture capitalists.

Recently, another venture financing mechanism emerged: crowdfunding. Thanks to the possibilities that the internet has to offer, entrepreneurs quickly leveraged the benefits of raising capital via a random crowd of individuals willing to invest in a project. Crowdfunding platforms allow individuals to invest in projects in exchange for different offerings, typically ranging from equity shares, early prototypes, to discounts for future products (Piva & Rossi-Lamastra, 2018; Arshad, 2021; Wang, Li, Liang, Ye, & Ge, 2018). Commonly known as "backers", these types of investors demand higher transparency of the value of the product or service in order to feel connected to the brand, making it largely an emotional decision to drive their support (Yi, Luo, Feng, Wang, Feng & Yang, 2022). According to existing literature, the success of crowdfunding campaigns is also impacted by the human capital present in the founding team (Ahlers, Cumming, Günther & Schweizer 2015; An & Kim 2019; Barbi & Mattioli, 2019; Lim & Busenitz, 2020; Piva & Rossi-Lamastra, 2018).

Overall, the literature suggests that human capital does play a crucial role for investors (Ahlers et al. 2015; Honjo, 2021) that conduct due diligence, such as business angels, venture capitalists, and investors that typically require collateral, such as bank institutions (Robb & Robinson, 2014). Clearly, human capital has played a strong role in informing investors of key characteristics of entrepreneurs; proving how strongly human capital is associated with successfully securing financing.

2.2.2. Information Asymmetries & Signaling Theory

Although we emphasized the importance of sufficient financing in a prior section of our study, new ventures face several challenges in securing financial resources via external capital providers, especially in high-tech industries (Carpenter & Petersen, 2002; Ang, 1991). One of the main reasons that are causing these issues in financing new ventures is the information asymmetries that exist between entrepreneurs and investors.

Information asymmetry is a situation in which two parties have different degrees of information, in terms of quality and quantity. Investors generally have less information at their disposal than entrepreneurs about their ventures, notably due to the lack of track record. This results in investors relying on incomplete or hidden information to make their investing decisions. This information asymmetry between entrepreneurs and investors has been cited by scholars as one of the main causes of financial constraints for new ventures (Landström, 2017 cited in Glücksman, 2020; Wilson, Wright & Kacer, 2018).

In order to reduce the information asymmetry between these two parties, founders send signals to investors to inform them about the potential future performance of the firm and increase the likelihood to access financing. This concept is known as signaling theory (Spence, 1973 cited in Fisch, 2019). A common signal that entrepreneurs use to cope with the liability of the newness of their start-ups and reduce information asymmetry is their human capital (Glücksman, 2020). Given the information asymmetry between entrepreneurs and investors, founders' human capital serves as valuable information for investors to decide whether to fund a business and how much to invest (Honjo, 2021; Ko & McKelvie, 2018). In this sense, human capital represents key information when addressing information asymmetries.

In the context of TS, information asymmetry is particularly severe (Chen, 2019; Chen & Chen, 2020; Fisch, 2019), and arguably even more important to address than in traditional capital acquisition methods. The reasons for this particularly high degree of information asymmetry are twofold. First, Chen and Chen (2020) explain that this high information asymmetry is due to the lack of required capabilities from investors to interpret technical signals, such as quality source code and other details necessary to comprehend WPs. Second, the lack of regulations, and therefore the absence of formal disclosures, coupled with the desire for anonymity in the context of ICOs (Fisch et al., 2021), creates uncertainty from the investor's perspective (Fisch, 2019). Thus, the need for signals arises as a crucial dimension in ICO fundraising.

Scholars have studied multiple signals in the context of ICOs (Yadav, 2017), such as quality source code and other technical aspects of the white paper (Fisch, 2019; Moro & Wang, 2019; Giudici, Adhami, Martinazzi, 2018; Florysiak & Schandlbauer, 2022), team characteristics (Burns & Moro, 2018, Burns & Moro, 2019; Fenu, Marchesi, Marchesi, Tonelli, 2018; Giudici & Adhami, 2019), and investor perspectives (Fisch et al., 2019).

The human capital of the founding team acting as a signal in the context of TS remains, to the best of our knowledge, unexplored by literature. Chen and Chen (2020) also emphasize the interest in exploring the founder characteristics in the success of ICOs. Fisch (2019) echoes the importance of further research to explore the potential influence of human capital on the outcome of ICOs.

2.3. Breakdown of Human Capital From an Entrepreneurial Perspective

2.3.1. General and Specific Human Capital

The literature suggests that human capital is composed of two main aspects: general human capital and specific human capital (Stucki, 2016; Becker, 1964 cited in Colombo & Grilli, 2005; Brüderl, Preisendörfer & Ziegler, 1992).

General human capital refers to general knowledge that can be transferred in different environments (Sturman, Walsh & Cheramie, 2008). Founders acquire this general knowledge through formal education and informal experiences (Colombo, Delmastro & Grilli, 2004).

Common examples of general human capital include training, courses, degrees, and other learned information. Thence this knowledge is applicable in different entrepreneurial settings. Founders can start a venture in diverse industries and take advantage of this type of human capital regardless of the specific context (Baptista, Karaöz & Mendonça, 2014).

Specific human capital, on the other hand, is a type of human capital that refers to targeted learned information that is relevant to one's organization, industry, or job role (Colombo, Delmastro & Grilli, 2004). These skills are typically non-transferrable to other roles, workplaces, or industries. They can be directly applied to a certain environment, and are often learned for a specific role (Baptista, Karaöz & Mendonça, 2014; Honjo, 2021).

2.3.3. Role of Human Capital in Token Sales

Clearly, research shows a strong relationship between human capital and access to capital via traditional financing mechanisms. Human capital provides investors a signal that reduces information asymmetries and helps them decide whether to invest in a start-up, which typically does not carry any track records that would assist in making investing decisions.

The emergence of blockchain technology opens up possibilities for innovative ways to raise capital, thus allowing entrepreneurs to access large amounts of funding in order to develop their ventures. Token sales address the challenges that these types of ventures are facing, constituting a major innovation for entrepreneurial finance. However, due to the newness of this phenomenon, limited literature has been found on the relationship between the founding team's human capital and its ability to access financing in the early stages. On that account, our study focuses on investigating the potential impact of the human capital of entrepreneurs and their ability to raise funds via TS, particularly concerning ICOs.

3. Methodology

This section aims to provide a presentation of our methodological approach. This includes an overview of the research design, the acquisition of empirical data, and selected samples. This is followed by operational definitions and measures, and data analysis. We end this part of our work with descriptive statistics and other statistical tests to verify the quality of the data used.

3.1. Research Design

By conducting an analysis of European ICOs between the years 2016 and 2021, we use an explorative approach to attempt to answer our research question:

"*Does the founding team's human capital have an impact on token sale success?*"

We perform multiple logistic regressions to observe the relationship between human capital and ICO success. In order to do that, this research takes advantage of a recent database that compiles data from several thousands of token sales.

We believe this area of study deserves further attention since limited empirical studies exist about the founding teams who conduct ICOs. Doing so may offer an indication of other signals that entrepreneurs can use to reduce information asymmetry in this context. Chen and Chen (2020) emphasize the need for further research by insisting: "It will be interesting to explore the role of characteristics of entrepreneurial founder teams in the success of ICOs, such as their past experiences [...]". The newness of this phenomenon may explain the lack of research in this particular field.

3.2. Data Collection

The data used in this study comes from a database collected between February 2021 and August 2021. The dataset is composed of more than 17,000 observations of ICOs that occurred worldwide between 2016 and 2021. Hence, almost the entirety of ICOs that happened during that period was gathered into this database, allowing us to benefit from a very comprehensive dataset.

It should be remembered that ICOs are the most common type of TS. Other TS types appeared only over the last few years. We are not aware of any database that distinguishes TS types. The data used for this research takes ICOs as an inclusive term for other TS types. The distinction of those TS types is not relevant for our study. Hence, in the following section, TS refers to the observations of ICOs from the database. There is, to the best of our knowledge, no other database that compiles this magnitude of observations and collects such a scope of information about the founding team's human capital.

3.3. Sample

We narrowed down our research to ICOs that occurred in Europe in order to increase the homogeneity of observations, hence reducing our sample to a dataset of approximately 2,000 observations. We narrowed the sample further by removing observations that lacked any specified ICO industry. Subsequently, we deleted observations containing ICO industries that did not have matching skills available in the dataset. As an example, the ICO industry called "health and medicine", which did not have corresponding skills in relation to the founding team, was removed from the sample. By doing so, we solidified the likelihood of a stronger relationship between the founding team's skills and the start-up's industry. Thus, our final sample comes to 1185 observations.

We also selected a set of variables that support the objective of our study. These variables are presented and explained in the next section.

3.4. Operational Definitions and Measures

The literature distinguishes two aspects of human capital, particularly when it comes to entrepreneurs: general human capital and specific human capital (Honjo, 2021). On one hand, general human capital represents the general knowledge that can be transferred across various environments, such as education (Sturman, Walsh & Cheramie, 2008). On the other hand, specific human capital refers to industry-specific experiences and skills that are relevant to one's organization, industry, or role (Colombo, Delmastro & Grilli, 2004). We selected variables that correspond to the best extent possible to both of these aspects of human capital.

First, general human capital is represented through the highest degree obtained by the CEO, CTO, and CFO (no higher education title, bachelor, master, or Ph.D.) (Ko & McKelvie, 2018). Typically in Europe, a bachelor's degree requires 3 years, a master's degree requires 5 years, and a Ph.D. requires 8 years. Taking these standards, we sum the number of years spent at a higher education institution for each person in the team. Hence, the founding team accumulates general knowledge from each additional team member. As an example, an ICO team with a CEO who holds a bachelor's degree (3 years) and a CFO who holds a master's degree (5 years) reaches an education level of 8 (= 3 + 5). In other words, the general human capital is aggregated by the total number of years of higher education obtained by the overall team.

Second, in our study, specific human capital is measured through the industry-related skills that are shown on the LinkedIn profiles of the CEO, CTO, and CFO (Ko & McKelvie, 2018). Each team member who has a background with relevant skills that match the ICO's industry adds one point to the score of the overall team. By relevant skills, we mean any skill that falls under the same ICO industry category. As an example, if the ICO's industry is into finance and the CEO shows two finance-related skills on LinkedIn (2 relevant skills) and the CFO of the same team shows three finance-related skills (3 skills), then the specific human capital of the team reaches a total of 5 (= 2 + 3). This allows us to take the whole team's relevant skills into account.

As a dependent variable, we use the success of the ICO, which is represented by a discrete, dummy variable (0 = fail, 1 = success). A successful ICO is defined by meeting the minimum funding goal mentioned in the white paper, regardless of the amount, which is typically called a "soft cap". Using the success of the ICO as a dependent variable instead of the amount of funds raised removes gaps of missing data concerning what the funds were used for, the amount of funds needed, and other confounding variables. We intend to measure the relationship between human capital and the ability to raise funds via token sales. ICO success provides a variable that represents this ability.

In order to improve the significance of our models by explaining the dependent variable through multiple aspects, we defined control variables that have been explored by scholars, and if they have an effect on ICO success. Although Fenu et al. (2018) studied the impact of team size on ICO success and found that it does contribute to either success or failure of the ICO, Burns and Moro (2018) found that there is a positive correlation to the amount raised in an ICO. Therefore, we selected the size of the team as the first control variable of our regression models. The second control variable is related to the social media aspect of the ICO. The idea that social media impacts ICO success is supported by Xuan, Zhu, and Zhao (2020).

The following table gives an overview of all the variables that are included in our research:

Variable Name	Variable Description
Education_Level_Team	Total education level of the CEO, CTO, and CFO according to the years spent in higher education.
Relevant_Skills_Team	Total skills of the CEO, CTO, and CFO that match the ICO's industry.
Team_Size	The number of people in the team.
TwitterFollower	The number of Twitter followers for the ICO's project.
TelegramFollower	The number of Telegram followers for the ICO's project.
FacebookFollower	The number of Facebook followers for the ICO's project.
Dummy_Success	Binary outcome (0 = fail, 1 = success) if the ICO's project reached the minimum funding goal.

Figure 3: Variable names and definitions.

3.5. Data Analysis

The data will be analyzed under a quantitative lens using the statistical software Stata. We will use the logistic regression model to observe data provided from the sample set as we seek to study the relationship between the founding team's human capital and the success of the token sale (ICO).

The logistic regression measures binary occurrences (Hosmer & Lemeshow, 2000) of yes/no, pass/fail, etc., which fits into the dependent variable we use (ICO's success: fail = 0, success = 1). The logistic regression model is used to examine the probability of the relationship between general or specific human capital and the success of the ICO. The founding team's education level score (as a measure of general human capital) constitute the independent variable in our first regression, the founding team's overall relevant skills (as a measure of specific human capital) constitutes another independent variable for our second regression, and the ICO's success (as a measure for the ability of the entrepreneurs to raise capital) is used as a dependent variable in all models. Finally, both independent variables are used together in a third model to analyze the influence of human capital on the dependent variable.

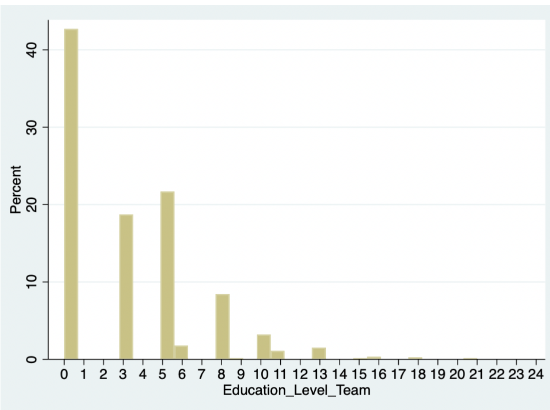
3.6. Descriptive Statistics & Statistical Tests

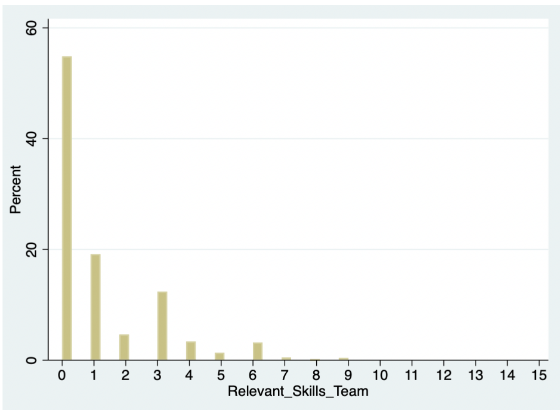
To give the reader an overview of the data, Figure 4 presents descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Dummy_Succ~s	1,185	.4540084	.4980905	0	1
Education_~m	1,185	3.204219	3.508024	0	21
Relevant_S~m	1,185	1.131646	1.700423	0	9
Team_size	1,185	11.49789	5.80673	1	20
TwitterFol~r	952	5244.69	11510.95	2	194219

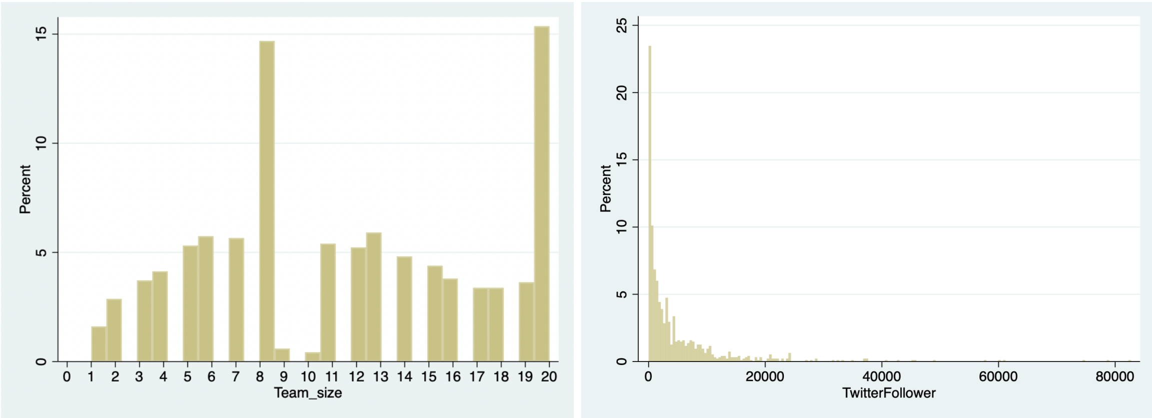
Figure 4: Descriptive statistics.

The following figures describe the distribution of both the independent and control variables used in this study.





Figures 5 and 6: Distribution of the level of education and the relevant skills for the ICO of the overall team.



Figures 7 and 8: Distribution of the size of the teams and the number of Twitter followers.

We check for multicollinearity by first utilizing the Pearson r-correlations. None of the variables are concerning in terms of collinearity, as Figure 9 shows. According to Senaviratna and Cooray (2019), values that stay below 0.8 or 0.9 do not raise any concern for multicollinearity. To ensure the lack of collinearity between all variables we use in our different models, we also perform the variance inflation factor (VIF). The results shown in Figure 10 highlight that our variables do not suffer from any collinearity, as none of our values exceed the threshold of 10 or even 2.5, which is often used for weaker regression models (Senaviratna & Cooray, 2019).

	Dummy_~s	Educat~m	Releva~m	Team_s~e	Twitte~r
Dummy_Succ~s	1.0000				
Education_~m	-0.0065	1.0000			
Relevant_S~m	-0.0052	0.1705	1.0000		
Team_size	0.1784	0.0680	0.0440	1.0000	
TwitterFol~r	0.1690	0.0192	-0.0122	0.1290	1.0000

Figure 9: Correlation between the variables we used across our research process.

Variable	VIF	1/VIF
Team_size	2.07	0.482089
Education_~m	1.76	0.567473
Relevant_S~m	1.49	0.670630
TwitterFol~r	1.22	0.818207
Mean VIF	1.64	

Figure 10: Variance inflation factor.

4. Results

This section presents and describes the results of our multiple logistic regressions. First, three models are presented analyzing general and specific human capital in relation to ICO success. In each model, we run a logistic regression with the independent variables we selected earlier and the control variables.

<u>Model I: General human capital</u>

This model evaluates the impact of the education level of the CEO, CTO, and CFO of each team in relation to the success of the ICO.

<u>Model II: Specific human capital</u>

This model evaluates the impact of the relevant skills endorsed via LinkedIn of the CEO, CTO, and CFO of each team in relation to the success of the ICO.

<u>Model III: General and specific human capital</u>

This model takes the independent variables of both Model I and Model II to evaluate the impact of human capital as a whole on ICO success.

In a second phase, we separate the lower and upper quartiles of observations in terms of Twitter followers. Our intention is to assess the effect of human capital on TS success based on an aspect (Twitter followers) that has proven to have a significant influence on ICO success.

4.1. Control Variables

Based on the variables available from the database, we have selected four potential control variables that seem to influence the success of ICOs, according to the existing literature. This constitutes the starting point of our selection of control variables.

First, scholars have studied the effect of team size on the success of ICOs (Fenu et al. 2018). In their studies they show that team size was not relevant to ICO success, however, there are several limitations to their study. A major limitation was their definition of “successful ICOs”, which were only defined as such if each ICO had raised at least 200,000 USD. Hence, this observation does not fit our definition of ICOs’ success previously explained in section 3.4. (Operational Definitions). However, Burns and Moro (2018) found that there is a positive correlation between the amount of funds raised in an ICO and team size. Building further on this research, we tested the impact of team size on ICOs' success from our dataset and found out that team size is statistically significant. Hence, we use this as a control variable in our regressions because it partially explains the success of ICO.

Second, Xuan, Zhu, and Zhao (2020) studied the influence of social media on the success of ICOs and their findings suggest that social media use influences the ability of teams to secure capital and the outcome of the ICOs. Starting from this, we wanted to see the influence of social media followers on the success of ICOs in our dataset and found out that the number of Twitter followers is statistically significant.

Logistic regression	Number of obs = **648**
	LR chi2(**4**) = **43.75**
	Prob > chi2 = **0.0000**
Log likelihood = **-426.28412**	Pseudo R2 = **0.0488**

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Team_size	**1.046984**	**.0157517**	**3.05**	**0.002**	**1.016562**	**1.078317**
TwitterFollower	**1.000053**	**.0000147**	**3.60**	**0.000**	**1.000024**	**1.000082**
TelegramFollower	**.9999967**	**7.88e-06**	**-0.42**	**0.677**	**.9999813**	**1.000012**
FacebookFollowers	**1.000008**	**4.72e-06**	**1.64**	**0.101**	**.9999985**	**1.000017**
_cons	**.4546127**	**.0933176**	**-3.84**	**0.000**	**.3040303**	**.6797769**

Note: **_cons** estimates baseline odds.

Figure 11: Control variables and their effect on ICO success.

According to our control variables regression model, both Team_size and TwitterFollower variables have a significant effect on the outcome, which is the success of ICOs. Indeed, *p*-values are 0.002 and 0.000 respectively, which is less than 0.05. Given this significance, we employ these variables as control variables in our subsequent regressions (Models I, II, and III). According to Figure 11, none of the other explanatory variables have proven to have a significant influence on ICO success, therefore we forgo including these variables.

4.2. Model I

Logistic regression				Number of obs =	952	
				LR chi2(3) =	63.85	
				Prob > chi2 =	0.0000	
Log likelihood = -627.81435				Pseudo R2 =	0.0484	

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Education_Level_Team	.985548	.0186102	-0.77	0.441	.9497395	1.022707
Team_size	1.056351	.0127658	4.54	0.000	1.031625	1.08167
TwitterFollower	1.000053	.0000113	4.73	0.000	1.000031	1.000075
_cons	.4083684	.0686087	-5.33	0.000	.2937949	.5676229

Note: **_cons** estimates baseline odds.

Figure 12: Education level of the overall team related to the success of ICOs, with control variables.

According to Figure 12, our logistic regression model is significant (Prob > chi2 = 0.000), as the outcome is explained through the explanatory variables used in the model. The coefficient for the independent variable of education of the overall team (0.985548) means that every additional year of education in a team increases the odds of having a successful ICO by 2.679 (= $e^{0.985548}$). Alternatively, every marginal year of education increases the likelihood of reaching the soft cap (successful ICO) by 167.927%. However, this relationship is not significant as the *p*-value = 0.441. Hence, we are not able to verify any effect of the education of the overall team on the ICO success. The general human capital does not significantly impact the success of ICO.

4.3. Model II

```
Logistic regression                                     Number of obs =    952
                                                        LR chi2(3)    =  63.38
                                                        Prob > chi2   = 0.0000
Log likelihood = -628.04919                             Pseudo R2     = 0.0480
```

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Relevant_Skills_Team	.986344	.038337	-0.35	0.724	.9139955	1.064419
Team_size	1.055846	.0127363	4.51	0.000	1.031176	1.081106
TwitterFollower	1.000053	.0000113	4.72	0.000	1.000031	1.000075
_cons	.398846	.0661322	-5.54	0.000	.2881831	.5520037

Note: **_cons** estimates baseline odds.

Figure 13: Relevant skills of the overall team related to the success of ICOs, with control variables.

According to Figure 13, our logistic regression model is significant, (Prob > chi2 = 0.000). The coefficient for the independent variable of skills of the overall team (0.986344) means that every additional relevant skill among team members increases the odds of having a successful ICO by 2.681 (= $e^{0.986344}$). Alternatively, every relevant skill related to the ICO industry in the team increases the likelihood of reaching the soft cap (successful ICO) by 168.141%. However, this relationship is not significant as the *p*-value = 0.724. Thus, we are not able to verify any effect of relevant skills of the overall team on the success of the ICO. The specific human capital does not significantly impact the success of ICO.

4.4. Model III

Logistic regression	Number of obs = **952**
	LR chi2(4) = **63.91**
	Prob > chi2 = **0.0000**
Log likelihood = **-627.78839**	Pseudo R2 = **0.0484**

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf. interval]	
Education_Level_Team	**.9862684**	**.0188901**	**-0.72**	**0.470**	**.9499307**	**1.023996**
Relevant_Skills_Team	**.9910573**	**.0390758**	**-0.23**	**0.820**	**.9173546**	**1.070681**
Team_size	**1.056444**	**.0127739**	**4.54**	**0.000**	**1.031702**	**1.08178**
TwitterFollower	**1.000053**	**.0000113**	**4.73**	**0.000**	**1.000031**	**1.000075**
_cons	**.4114615**	**.070442**	**-5.19**	**0.000**	**.2941737**	**.5755122**

Note: **_cons** estimates baseline odds.

Figure 14: Education level and relevant skills of the overall team related to the success of ICOs, with control variables.

According to Figure 14, our logistic regression model is significant (Prob > chi2 = 0.000). The coefficients for the independent variables of both education and relevant skills of the overall team are 0.9862684 and 0.9910573, respectively. This suggests that both these aspects of human capital increase the odds of having a successful ICO by 2.681 (= $e^{0.9862684}$) and 2.694 (= $e^{0.9910573}$). Alternatively, every marginal year of education or relevant skills related to the ICO industry in each team increases the likelihood of reaching the soft cap (successful ICO) by 168.121% and 169.408%, respectively. However, this relationship is not significant, as *p*-values = 0.470 and 0.820. Hence, we are not able to verify any effect of both the education of the overall team and the relevant skills of all team members together on the ICO success. According to our findings, both general and specific human capital do not significantly impact the success of ICO.

4.5. Analysis of Extreme Quartiles

In this section, we build further upon our previous research by exploring the lower and upper quartiles of our sample in terms of the number of Twitter followers (TwitterFollower).

4.5.1. Lower Quartile Analysis

```
Logistic regression                                     Number of obs =    238
                                                        LR chi2(2)    =   2.83
                                                        Prob > chi2   = 0.2431
Log likelihood = -137.14195                             Pseudo R2     = 0.0102
```

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Education_Level_Team	.9558915	.0415106	-1.04	0.299	.8778984	1.040814
Team_size	1.038385	.0272925	1.43	0.152	.9862475	1.093279
_cons	.2919197	.0932828	-3.85	0.000	.1560495	.5460902

Note: _cons estimates baseline odds.

Figure 15: Education level of the overall team related to the success of ICOs, within the lower quartile of Twitter followers.

```
Logistic regression                                     Number of obs =    238
                                                        LR chi2(2)    =   3.79
                                                        Prob > chi2   = 0.1501
Log likelihood = -136.66008                             Pseudo R2     = 0.0137
```

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Relevant_Skills_Team	.861098	.0929757	-1.39	0.166	.6968599	1.064044
Team_size	1.036304	.0269574	1.37	0.170	.9847932	1.09051
_cons	.3001918	.0946962	-3.81	0.000	.1617653	.5570735

Note: _cons estimates baseline odds.

Figure 16: Relevant skills of the overall team related to the success of ICOs, within the lower quartile of Twitter followers.

Logistic regression		Number of obs =	238
		LR chi2(3) =	4.75
		Prob > chi2 =	0.1910
Log likelihood = -136.18071		Pseudo R2 =	0.0171

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Education_Level_Team	.9586266	.0420667	-0.96	0.336	.8796236	1.044725
Relevant_Skills_Team	.8649291	.0940934	-1.33	0.182	.6988444	1.070485
Team_size	1.039718	.0273476	1.48	0.139	.9874759	1.094724
_cons	.3308635	.1096483	-3.34	0.001	.1728067	.6334864

Note: **_cons** estimates baseline odds.

Figure 17: Education level and relevant skills of the overall team related to the success of ICOs, within the lower quartile of Twitter followers.

Interestingly, when we narrow down the sample to the lower quartile of the number of Twitter followers (TwitterFollower), the significance of the three models presented decreases with Prob > chi2 lower than 0.05 (= 0.2341, 0.1501, and 0.1910, respectively). However, the significance of our independent variable representing general human capital increases, as education's *p*-value = 0.299, albeit still not statistically significant. Concerning the specific human capital, the same applies to the relevant skills of the founding team's *p*-value = 0.166, which is marginally more significant than in previous models. The significance of both general and specific human capital increases compared to Model I and II, from our initial sample that includes all observations. When both general and specific human capital are components of our logistic regression models, their *p*-values equal 0.336 and 0.182 respectively, which shows higher significance than Model III in comparison. Finally, we observe that the human capital of the teams within the lower quartile of Twitter followers displays higher significance in comparison to the initial sample.

4.5.2. Upper Quartile Analysis

```
Logistic regression                                     Number of obs =    238
                                                        LR chi2(2)    =   2.65
                                                        Prob > chi2   = 0.2664
Log likelihood = -153.1982                              Pseudo R2     = 0.0086
```

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Education_Level_Team	1.021536	.0365646	0.60	0.552	.9523263	1.095775
Team_size	1.03841	.0253698	1.54	0.123	.9898577	1.089344
_cons	1.002369	.3939899	0.01	0.995	.4639335	2.165708

Note: **_cons** estimates baseline odds.

Figure 18: Education level of the overall team related to the success of ICOs, within the upper quartile of Twitter followers.

```
Logistic regression                                     Number of obs =    238
                                                        LR chi2(2)    =   2.35
                                                        Prob > chi2   = 0.3092
Log likelihood = -153.34727                             Pseudo R2     = 0.0076
```

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Relevant_Skills_Team	1.019508	.080456	0.24	0.807	.8734074	1.190048
Team_size	1.037018	.0253463	1.49	0.137	.9885111	1.087905
_cons	1.078571	.3983515	0.20	0.838	.5229648	2.224464

Note: **_cons** estimates baseline odds.

Figure 19: Relevant skills of the overall team related to the success of ICOs, within the upper quartile of Twitter followers.

```
Logistic regression                                     Number of obs =    238
                                                        LR chi2(3)    =   2.66
                                                        Prob > chi2   = 0.4479
Log likelihood = -153.19341                             Pseudo R2     = 0.0086
```

Dummy_Success	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
Education_Level_Team	1.020618	.0377209	0.55	0.581	.9493002	1.097293
Relevant_Skills_Team	1.007992	.0820566	0.10	0.922	.8593381	1.18236
Team_size	1.038159	.0254888	1.53	0.127	.9893848	1.089338
_cons	.9988687	.3942199	-0.00	0.998	.4608587	2.164956

Note: **_cons** estimates baseline odds.

Figure 20: Education level and relevant skills of the overall team related to the success of ICOs, within the upper quartile of Twitter followers.

Similar to the Lower Quartile Analysis, the Upper Quartile Analysis shows the significance of the Figures 18, 19, and 20 decreases with a Prob > chi2 lower than 0.05 (= 0.2664, 0.3092, and 0.4479, respectively). Furthermore, the *p*-value of the variable representing general human capital, i.e. education, increases with the sample of the upper quartile of Twitter followers, compared to Model I. This suggests a lower significance than in Model I. Concerning the independent variable representing specific human capital, the same observation applies as the *p*-value increases to 0.992, which is also higher than in Model II. Looking at Figure 20, both aspects of human capital, i.e. general and specific, have a smaller significance compared to our logistic regression for our initial sample (Model III). Overall, these findings suggest that human capital (both general and specific) has less significance when the number of Twitter followers is higher.

In summation, all *p*-values for the independent variables in the lower quartile, i.e. education and relevant skills, show higher significance in relation to ICO success than in the upper quartile. By comparing the lower and upper quartile, our results suggest a clear pattern, which is that human capital has a more significant impact on ICO success when ICOs have fewer Twitter followers.

5. Discussion

We expected human capital to play a role in ICO funding as it did for traditional financing, which was explained in the theoretical framework of this paper. However, the results of our research do not significantly show any effect of human capital on ICO success. Our results suggest that general human capital's influence (education) is not statistically significant on ICO success. The same evidence is found for specific human capital (relevant skills), which does not significantly affect ICO success according to our empirical research. The overall human capital, composed of both general and specific types, is not significant in relation to ICO success, which answers our research question. To sum up, our study does not show a significant relationship between the human capital of the founding team and the success of the ICO.

Surprisingly, our findings suggest that social capital, particularly the number of Twitter followers, plays a significant role in securing ICO financing and reaching the funding goal. Team size has also proven to have a significant effect on ICO success, leaving room for further research on the effect of human capital on ICO funding.

Additionally, we looked at the lower and upper quartile in terms of Twitter followers to see if there was any difference between the ICO projects that have a high number of followers and the ones that do not. Interestingly, our results suggest that human capital has a significantly stronger influence on ICO funding with fewer followers on Twitter. This may imply that when signals like social network followers are weak, investors may potentially look for alternative signals, such as the human capital of the team.

Possible explanations of the results presented above are discussed in the next section.

5.1. Potential Explanations of Results

Token sales differ from traditional financing methods in the sense that they disintermediate venture financing, allowing a new pool of less informed micro-investors to fund a start-up. Understanding the behavior of these new types of investors is crucial to addressing the dynamics of a novel disruptive financial market. These new investors react to different signals than traditional early-stage capital providers (Fisch, Masiak, Vismara, and Block, 2021). In the present section, we provide potential explanations of our results which were presented in part 4 of this study.

Herd Behavior

Given the effect of Twitter followers on our results, coupled with the absence of influence of human capital related to ICO success, we consider that herd behavior potentially explains this observation. There are various studies examining the nature of this phenomenon in many settings, including finance. In behavioral finance, herd behavior is a concept that refers to “a decision-making approach characterized by imitating the actions of others” (Hotar, 2020, p. 81). Mattke, Maier, Reis, and Weitzel (2020, p. 3) studied herd behavior in the context of social media, and go on to say that “herd behavior describes the phenomenon of how a user is influenced by observing others’ prior behavior and imitates this behavior even if their own information supports a different behavior”. Gul and Khan (2019) also argue that herd behavior consists of a psychological bias that alters investors' investment decisions, which opposes rational assessment typically exercised in traditional finance. Specifically, in our study, ICO investors that follow rational behavior would pay attention to the human capital of the team, as studies have shown that this affects the future performance of the project (Honjo, 2021). Rather, our results suggest that they tend to follow a potential herd behavior by investing in ICOs with the highest number of Twitter followers, hence, imitating the behavior of other individuals. In other words, herding encourages individuals, specifically investors in our study, to simulate the market consensus instead of relying on their investment decisions on personal assessments (Gul & Khan, 2019). According to Hotar (2020), in the environment of cryptocurrencies, in which ICOs are embodied, markets are highly dependent on social aspects. The author argues that individuals who participate in the cryptocurrency markets tend to be “young, inexperienced investors who are easily influenced by social media” (p. 80). Fisch et al. (2021) support this potential explanation by explaining that the “hype effect” may motivate ICO investors without strong knowledge of finance or tech to micro-invest in multiple ICOs. They conclude by arguing that herding behavior seems to play a significant role in the ICO market. To summarize, ICO investors may follow the choice patterns of their peers rather than employing knowledge available to them, which suggests the presence of herd behavior in ICOs.

Lack of Due Diligence

White papers are the main sources of information for ICOs (Florysiak & Schandlbauer, 2022). However, due to the lack of a regulatory framework concerning TS in general, WPs do not require any specific information. As a consequence, WPs are usually missing relevant information for investors or are difficult for them to understand (Burns & Moro, 2019; Chen & Chen, 2020), as investors are typically non-professional (Fisch et al., 2021). What is also emphasized in Fisch et al. (2021) is that there is a common will for anonymity in the context of cryptos and ICOs, which enables entrepreneurs to not mention their identity or their background. All these aspects of WPs make human capital unlikely to appear in the information that the crowd of online investors has access to. Additionally, even when a WP discloses information about the team, some investors do not read it (Fisch et al., 2021). The fact that WPs are usually complex to read may be one reason for that, but another potential explanation of why investors do not read the WP properly could be due to the smallness of the investment. A substantial portion of ICO investors support projects by doing micro-investments (Fisch et al., 2021), and are not willing to conduct thorough due diligence because the cost of information might be larger than the potential marginal return. This profile of investors typically corresponds to individuals who are prone to more risk (Fisch et al., 2021). As a consequence, investors tend to not look at human capital or are unable to find information about it. Overall, this leads to a lack of proper due diligence (Yadav, 2017) concerning the individuals behind the ICO and the human capital of the team.

These two alternative interpretations of our results do not exhaustively list the breadth of explanations, rather, they provide the reader with an overview of how the findings of this study can be discussed. These are also explanations that are supported by existing literature.

The following section provides the limitations of our research.

5.2. Limitations

Our work contains several limitations that should be taken into account when interpreting the results mentioned above, which should nuance our findings.

5.2.1. Methodological Limitations

One of the main methodological limitations of this study refers to the absolute definition of general human capital, which is only measured by the number of years of education. This neglects to observe other aspects of general human capital, one of them being the quality of education. This may entail the quality of the university attended, the rigor of the program, or the relation of the degree obtained to the ICO project. In addition, we approximate general human capital by the years of education of the overall team, which may lead to less precise results. However, general human capital, which is defined in literature as a set of knowledge that is transferable from one organization, industry, or position to another (Sturman, Walsh & Cheramie, 2008), is not limited to only counting the years in higher education. We believe other factors such as soft skills, hard skills learned independently, and other means still fit within the framework of general human capital.

Similarly, specific human capital is limited in our study because we only measure it through LinkedIn skills, which is a self-ascribed attribute. It does not consider the number of endorsements, whether they chose to build their skills section or people who don't have a LinkedIn profile. There is also a limitation in the approach of choosing what skills are relevant when in reality, multiple skills from various fields can contribute to professional competency. Indeed, we defined relevant skills as the skills that perfectly match the ICO's industry. Furthermore, specific human capital can be measured in more ways than explicitly LinkedIn skills, such as certificates earned, trade schools attended, independent courses, or other means of obtaining skill sets that cannot be observed only via LinkedIn.

An additional limitation to our study that is worth mentioning is the constrained number of control variables used to explain our dependent variable, i.e. ICO success. Indeed, we expect the success of TS to be explained through many other variables, which makes our model incomplete or limited. Adding more variables to the models presented may more thoroughly explain ICO success and increase the accuracy of our findings, hence solidifying the potential influence of human capital on ICO success.

Lastly, we evaluated the human capital of the team as a whole, rather than looking at individuals. Although this gave us the advantage of having a broader overview of the ICO teams, some limitations arose from this methodological decision. Certain projects may depend more heavily on one individual in particular whereas other supportive functions that are still in the team may be less relevant for the project. For example, a developer may hold higher importance in terms of work output in a tech venture. A solution to this problem could be to create weighted roles for the team depending on the project, but this implies a subjective assessment of both the project and the team.

5.2.2. Data Limitations

The database used for our research contains a significant portion of zeros or missing values for certain measures. This does not allow us to make the distinction between individuals who obtained a degree in higher education and the ones that did not disclose their academic background, for example. The reason for this possible lack of data may be due to the fact that ICOs and other TS lack a regulatory framework, thus not requiring the team to disclose anything about themselves. Although this limitation in terms of data highlights a weakness of our work, the program used to run the regressions present in this study (i.e. Stata) does not take missing values into account.

We have also found potential limitations concerning the data available from our database, and also from the platforms the original data was extracted from. First is the team size, which may have upper limits when submitting team information on certain platforms. This may be why there are particularly high numbers for team sizes 8 and 20 (see Figure 8). This may be due to options on platforms that say to choose “20 or more” team members when team size exceeds a certain limit.

The second database limitation is that the information pulled from team members only concerns the CEO, CTO, and CFO. Not only can a team have more members than this, but they may not have one of these three roles to begin with. A CFO, for example, may not be part of the team until a later stage in the start-up. An extension of this limitation is the fact that the founding team does not always correspond to the CEO, CTO and CFO. Indeed, this paper aggregates the founding team to these three positions. This definition constitutes a limitation of our work.

5.3. Further Research

The findings of this study, coupled with the limitations, suggest that further research should be conducted in order to more thoroughly understand the dynamics of ICOs, and more particularly the signals that reduce information asymmetry in the context of TS.

A possible interpretation of our findings is that WPs do not allow investors to learn about the human capital of the team behind the ICO. We believe that further research should be conducted to explore the potential influence of the human capital of the founding team on TS success by selecting a sample of ICOs with WPs that disclose the human capital of the team. By doing so, researchers could observe any potentially significant impact of human capital on TS success. Fisch (2019) researched how WPs affect ICO financing. Their findings suggest that WPs play a significant role in ICO fundraising. We suggest further research on this topic to see what elements of the WP increase the likelihood of having a successful ICO and having met the funding goal.

We believe studying the effect of human capital on ICOs can be further researched by looking at the highest quartile of investments to determine if larger funding amounts indicate a stronger commitment to addressing information asymmetry. Doing so may increase the likelihood of investors conducting proper due diligence. In a similar vein, looking at professional investors in ICOs may also indicate whether human capital represents a relevant signal to reduce information asymmetry between investors and entrepreneurs. Fisch et al. (2021) studied the ICO investors' perspective and their work gives a starting point to further investigate this specific topic.

We support further investigation into human capital; however, social capital may also play a significant role in TS success. Chen and Chen (2020) emphasize the importance of investors' social media interactions with the start-ups raising capital via ICOs. They suggest that the venture-investor relationship has been largely ignored in previous studies. The influence of both the project's social media and the founding team's social capital such as the community size, the involvement of the founding team on social media, and other behavior patterns of social media followers, would be fruitful to explore (Ante, Sandler & Fiedler, 2018; Burns & Moro).

Finally, crypto-markets and TS are evolving at a high pace due to rapidly changing technological developments. Studying TS from an entrepreneurial finance perspective is fundamental to understanding these innovative mechanisms to finance emerging start-ups. Providing a framework to support entrepreneurs, investors and legislators is necessary to enable the efficient use of blockchain technology and, hence, foster entrepreneurship. Therefore, we suggest continuing the study of signals to investors but with a focus on new types of TS, such as initial exchange offering (IEO) or security tokens offering (STO) (Kranz, Nagel & Yoo, 2019; Myalo, 2019).

6. Conclusion

The emergence of TS as a new financing mechanism, allowed by the latest technological developments in the field of blockchain technology, disrupts entrepreneurial finance (Chen, 2018). Token sales provide entrepreneurs with an innovative method to finance start-ups, but little is known about the dynamics of TS and what signals entrepreneurs can use to reduce the particularly high degree of information asymmetry present in TS, such as in ICOs. These phenomena have drawn the attention of scholars to understand the criteria for TS success (Burns & Moro, 2018; Burns & Moro, 2019; Amsden & Schweizer, 2019; Ante, Sandler & Fiedler, 2018; Fisch, 2019; Fenu et al., 2018; Giudici & Adhami, 2019).

This study aims to provide an empirically supported answer to the question "*Does the human capital of the founding team have an impact on token sale success?*". Through an explorative, quantitative approach on a sample of more than 1,000 European ICOs, the human capital of the project's team was found to not be significant in relation to ICO success. Both general human capital, measured through the higher education of the overall team, and specific human capital, measured through the LinkedIn skills of the overall team that correspond to the ICO's industry, have shown to not significantly impact ICO success. This suggests that investors base their investment decisions on criteria other than the team's human capital. This finding is interesting in the sense that this innovative financing mechanism does not follow traditional funding method dynamics, where human capital has had an effect on the start-up's ability to successfully secure capital. Therefore, we emphasize the need for scholars to further research this topic.

Our work contributes to the existing literature about TS from an entrepreneurial finance perspective. It adds to the field by exploring the potential impact of a signal, i.e. human capital, that is used in traditional financing methods to reduce information asymmetries; but this concept remains under-explored by existing literature in the context of TS (Chen & Chen, 2020; Fisch, 2019). This study differentiates itself from other works by exploring the influence of human capital on TS success in a novel way, analyzed specifically through the lens of general and specific human capital. Our study draws from one of the largest ICO databases available, to the best of our knowledge. Using this extensive data, we argue that additional TS signals should be investigated to further boost venture financing.

On one hand, we believe our work can help entrepreneurs better understand the dynamics of TS by demonstrating which signals should be used to reduce information asymmetries, hence increasing the likelihood of successfully securing the external capital required to meet funding goals. On the other hand, we also provide investors a framework that compels them to perform thorough due diligence to help them base their investment decisions. Additionally, we believe legislators can benefit from our work by understanding the underlying principles of ICOs and to what extent the lack of regulatory framework pivots from traditional entrepreneurial finance. Reducing information asymmetries in the context of TS is of crucial importance in order to finance more start-ups and democratize entrepreneurial finance (Chen, 2018; Fisch, Vismara & Meoli, 2020). As it was previously explained, the degree of information asymmetry is particularly high in the ICO environment, which highlights the need for legislators to address this challenge. Our study provides an insight into what signals are relevant in the context of ICOs, helping policymakers to understand what would boost entrepreneurship, and thus, economic growth. The final stakeholders that can benefit from our work are academics. We believe we open up the discussion for further research for scholars to explore the phenomenon of information asymmetry and how to address it in the context of TS.

References

Agarwal, R., Echambadi, R., Franco, A. M., & Sarkar, M. (2004). Knowledge Transfer through Inheritance: Spin-out generation, development, and survival, *The Academy of Management Journal*, vol. 47, no. 4, pp. 501–522

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in Equity Crowdfunding, *Entrepreneurship theory and practice*, vol. 39, no.4, pp. 955-980

Amsden, R., & Schweizer, D. (2019). Are Blockchain Crowdsales the New 'Gold Rush'? Success determinants of initial coin offerings, PhD thesis, Desautels Faculty of Management, McGill University, Available online: https://dx.doi.org/10.2139/ssrn.3163849 [Accessed on 18 May 2022]

An, J., & Kim, H. W. (2019). Investigating Signals on Equity Crowdfunding: Human capital, earlier investors, and social capital, *Asia Pacific Journal of Information Systems*, vol. 29, no. 2, pp. 283-307

Ang, J. (1991). Small Business Uniqueness and the Theory of Financial Management, *The Journal of Entrepreneurial Finance*, vol. 1, no. 1, pp.11–13

Ante, L., Sandner, P., & Fiedler, I. (2018). Blockchain-based ICOs: Pure hype or the dawn of a new era of startup financing, *Journal of Risk and Financial Management*, vol. 11, no. 4, p. 80

Arshad, N. (2021). Backers' Crowdfunding Journey – An engagement perspective, PhD thesis, Jönköping International Business School, Jönköping University Available online: https://www.diva-portal.org/smash/record.jsf?dswid=-8987&pid=diva2%3A1613302 [Accessed on 18 May 2022]

Baptista, R., Karaöz, M., & Mendonça, J. (2014). The Impact of Human Capital on the Early Success of Necessity Versus Opportunity-based Entrepreneurs, *Small Business Economics*, vol. 42, no. 4, pp. 831-847

Barbi, M., & Mattioli, S. (2019). Human Capital, Investor Trust, and Equity Crowdfunding, *Research in International Business and Finance*, vol. 49, pp. 1-12

Bates, T. (1990). Entrepreneur Human Capital Inputs and Small Business Longevity, *The review of Economics and Statistics*, pp. 551-559

Brüderl, J., Preisendörfer, P. & Ziegler, R. (1992). Survival Chances of Newly Founded Business Organization, *American Sociological Review*, vol. 57, no. 2, pp. 227-242

Bruns, V., Holland, D. V., Shepherd, D. A., & Wiklund, J. (2008). The Role of Human Capital in Loan Officers' Decision Policies, *Entrepreneurship Theory and Practice*, vol. 32, no. 3, pp. 485-506

Burns, L., & Moro, A. (2018). What Makes an ICO Successful? An investigation of the role of ICO characteristics, team quality and market sentiment, School of Management, working paper, Cranfield University

Burns, L., & Moro, A. (2019). The Rationality of ICO Investors: Social media hype vs. team quality, School of Management, working paper, Cranfield University

Carpenter, R. E., & Petersen, B. C. (2002). Capital Market Imperfections, High‐tech Investment, and New Equity Financing, *The Economic Journal*, vol. 112, no. 477, pp. F54-F72

Casarella, P., & Manfrè, C. (2019). Capital Raises, Initial Coin Offerings, and Token Sales, *Graziadio Business Review,* vol. 22, no. 1, p. 1, Available online: https://gbr.pepperdine.edu/2019/03/capital-raises-initial-coin-offerings-and-token-sales/ [Accessed on 18 May 2022]

Chen, K. (2019). Information Asymmetry in Initial Coin Offerings (ICOs): Investigating the effects of multiple channel signals, *Electronic Commerce Research and Applications*, vol. 36, p. 100858

Chen, Y. (2018). Blockchain Tokens and the Potential Democratization of Entrepreneurship and Innovation, *Business horizons*, vol. 61, no. 4, pp. 567-575

Chen, R. R., & Chen, K. (2020). A 2020 Perspective on "Information Asymmetry in Initial Coin Offerings (ICOs): Investigating the effects of multiple channel signals", *Electronic Commerce Research and Applications*, vol. 40, p. 100936

Cole, R., Cumming, D., & Li, D. (2016). Do Banks or VCs Spur Small Firm Growth?, *Journal of International Financial Markets, Institutions and Money*, vol. 41, pp. 60-72

Coleman, S. (2004). The Role of Education and Experience in Small Firm Access to Bank Loans: Is there a link?, *Journal of Business and Entrepreneurship*, vol. 16, no. 1, p. 1

Colombo, M. G., Delmastro, M., & Grilli, L. (2004). Entrepreneurs' Human Capital and the Start-up Size of New Technology-based Firms, *International journal of industrial organization*, vol. 22, no. 8-9, pp. 1183-1211

Colombo, M. G., & Grilli, L. (2005). Founders' Human Capital and the Growth of New Technology-based Firms: A competence-based view, *Research policy*, vol. 34, no. 6, pp. 795-816

De Clercq, D., Fried, V. H., Lehtonen, O., & Sapienza, H. J. (2006). An Entrepreneur's Guide to the Venture Capital Galaxy, *Academy of Management Perspectives*, vol. 20, no. 3, pp. 90-112

Fenu, G., Marchesi, L., Marchesi, M. & Tonelli, R. (2018). The ICO Phenomenon and Its Relationships with Ethereum Smart Contract Environment, 2018 International Workshop on Blockchain Oriented Software Engineering (IWBOSE), Available online: https://ieeexplore.ieee.org/abstract/document/8327568 [Accessed on 18 May 2022]

Fisch, C. (2019). Initial Coin Offerings (ICOs) to Finance New Ventures, *Journal of Business Venturing*, vol. 34, no. 1, pp. 1-22

Fisch, C., Masiak, C., Vismara, S., & Block, J. (2021). Motives and Profiles of ICO Investors, *Journal of Business Research*, vol. 125, pp. 564-576

Fisch, C., Meoli, M., & Vismara, S. (2022). Does Blockchain Technology Democratize Entrepreneurial Finance? An empirical comparison of ICOs, venture capital, and REITs, *Economics of Innovation and New Technology*, vol. 31, no. 1-2, pp. 70-89

Florysiak, D., & Schandlbauer, A. (2022). Experts or Charlatans? ICO analysts and white paper informativeness, *Journal of Banking & Finance*, vol. 139, p. 106476

Gimmon, E. (2008). Entrepreneurial Team‐starts and Teamwork: Taking the investors' perspective, *Team Performance Management: International Journal*

Giudici, G., & Adhami, S. (2019). The Impact of Governance Signals on ICO Fundraising Success, *Journal of Industrial and Business Economics*, vol. 46, no. 2, pp. 283-312

Giudici, G., Adhami, S., & Martinazzi, S. (2018). Why Do Businesses Go Crypto? An empirical analysis of initial coin offerings, *Journal of Economics and Business*, vol. 100, pp. 64-75

Glücksman, S. (2020). Entrepreneurial Experiences from Venture Capital Funding: Exploring two-sided information asymmetry, *Venture Capital*, vol. 22, no. 4, pp. 331–354

Grilli, L. (2019). There Must Be an Angel? Local financial markets, business angels and the financing of innovative start-ups, *Regional Studies*, vol. 53, no.5, pp. 620-629

Gul, F., & Khan, K. (2019). An Empirical Study of Investor Attitudinal Factors Influencing Herd Behavior: Evidence from Pakistan stock exchange, *Abasyn University Journal of Social Sciences*, vol. 12, no.1

Headd, B. (2003). Redefining Business Success: Distinguishing between closure and failure, *Small Business Economics*, vol. 21, no. 1, pp. 51-61

Honjo, Y. (2021). The Impact of Founders’ Human Capital on Initial Capital Structure: Evidence from Japan, *Technovation*, vol. 100, no. 102191

Hosmer, D. W., & Lemeshow, S. (2000). Applied Logistic Regression, Wiley Series in Probability and Statistics Texts and References Section

Hossain, M. S. (2021). What Do We Know about Cryptocurrency? Past, present, future, *China Finance Review International*, vol. 11, no. 4, pp. 552-572

Hotar, N. (2020). Herd Behavior In Terms Of Social Psychology: The example of crypto asset markets, *International Journal of eBusiness and eGovernment Studies*, vol. 12, no. 1, pp. 79-90

Kerr, W., & Nanda, R. (2009). Financing Constraints and Entrepreneurship, working paper, no. 15498, National Bureau of Economic Research

Kim, K., & Hann, I. H. (2019). Crowdfunding and the Democratization of Access to Capital — An Illusion? Evidence from housing prices, *Information Systems Research*, vol. 30, no. 1, pp. 276-290

Ko, E. J., & McKelvie, A. (2018). Signaling for More Money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development, *Journal of Business Venturing*, vol. 33, no. 4, pp. 438-454

Kranz, J., Nagel, E., & Yoo, Y. (2019). Blockchain Token Sale, *Business & Information Systems Engineering*, vol. 61, no. 6, pp. 745-753

Lim, J. Y. K., & Busenitz, L. W. (2020). Evolving Human Capital of Entrepreneurs in an Equity Crowdfunding Era, *Journal of Small Business Management*, vol. 58, no. 1, pp. 106-129

MacMillan, I. C., Siegel, R., & Narasimha, P. S. (1985). Criteria Used by Venture Capitalists to Evaluate New Venture Proposals, *Journal of Business Venturing*, vol. 1, no. 1, pp. 119-128

Mattke, J., Maier, C., Reis, L., & Weitzel, T. (2020). Herd Behavior in Social Media: The role of Facebook likes, strength of ties, and expertise, *Information & Management*, vol. 57, no. 8, p. 103370

McLean, S., & Deane-Johns, S. (2016). Demystifying Blockchain and Distributed Ledger Technology – Hype or Hero?, *Computer Law Review International*, vol. 17, no. 4, pp. 97-102

Mollick, E., & Robb, A. (2016). Democratizing Innovation and Capital Access: The role of crowdfunding, *California Management Review*, vol. 58, no. 2, pp. 72-87

Moro, A., & Wang, D. (2019). Fintech Projects and Initial Coin Offerings: A research note, *The Journal of Entrepreneurial Finance*, vol. 21, no.1, p. 2

Myalo, A. (2019). Comparative Analysis of ICO, DAOICO, IEO and STO, *Case Study, Finance: Theory and Practice*, vol. 23, no. 6, pp. 6–25

Natarajan, H., Krause, S., & Gradstein, H. (2017). Distributed Ledger Technology and Blockchain, World Bank, working paper, Available online: https://openknowledge.worldbank.org/handle/10986/29053 [Accessed on 18 May 2022]

Piva, E., & Rossi-Lamastra, C. (2018). Human Capital Signals and Entrepreneurs' Success in Equity Crowdfunding, *Small Business Economics*, vol. 51, no. 3, pp. 667-686

Robb, A. M., & Robinson, D. T. (2014). The Capital Structure Decisions of New Firms, *The Review of Financial Studies*, vol. 27, no.1, pp. 153-179

Rohr, J., & Wright, A. (2019). Blockchain-based Token Sales, Initial Coin Offerings, and the Democratization of Public Capital Markets, *Hastings LJ*, vol. 70, no. 463

Samieifar, S., & Baur, D. G. (2021). Read Me If You Can! An Analysis of ICO White Papers, *Finance Research Letters*, vol. 38, p. 101427

Senaviratna, N., & Cooray, T. (2019). Diagnosing Multicollinearity of Logistic Regression Model, *Asian Journal of Probability and Statistics*, vol. 5, no. 2, pp.1–9

Smart, G.H. (1999). Management Assessment Methods in Venture Capital: An empirical analysis of human capital valuation, *The Journal of Private Equity*, vol. 2, no. 3, pp. 29–45

Storey, D., & Greene, F. (2010). Small Business and Entrepreneurship, Essex: Pearson Education Limited

Stucki, T. (2016). How the Founders' General and Specific Human Capital Drives Export Activities of Start-ups, *Research Policy*, vol. 45, no. 5, pp. 1014–1030

Sturman, M., Walsh, K., & Cheramie, R. (2008). The Value of Human Capital Specificity Versus Transferability, *Journal of Management*, vol. 34, no. 2, pp. 290–316

Tapscott, D., & Tapscott, A. (2016). The Impact of the Blockchain Goes Beyond Financial Services, *Harvard Business Review*, vol. 10, no. 7

Tenca, F., Croce, A., & Ughetto, E. (2017). Business Angels Research in Entrepreneurial Finance: A literature review and a research agenda, *Journal of Economic Surveys*, vol. 32, no. 2

Van Auken, H. E., & Carter, R. B. (1989). Acquisition of Capital by Small Business, *Journal of Small Business Management*, vol. 27, no. 2, pp. 1

Vasilescu, L. (2019). Private Equity As Financing Source For Smes – An outlook, *Annals of University of Craiova - Economic Sciences Series*, vol. 1, no. 47, pp. 87-95

Wang, N., Li, Q., Liang, H., Ye, T., & Ge, S. (2018). Understanding the Importance of Interaction between Creators and Backers in Crowdfunding Success, *Electronic Commerce Research and Applications*, vol. 27, pp. 106–117

Wilson, N., Wright, M., & Kacer, M. (2018). The Equity Gap and Knowledge-based Firms, *Journal of Corporate Finance*, vol. 50, pp. 626-649

Xuan, M., Zhu, X., & Zhao, J. L., (2020). Impact of Social Media on Fundraising Success in Initial Coin Offering (ICO): An empirical investigation, 24th Pacific Asia Conference on Information Systems (PACIS 2020). Available online: https://scholars.cityu.edu.hk/en/publications/impact-of-social-media-on-fundraising-success-in-initial-coin-offering-ico(78f7e950-04ea-4bc2-8eaf-53d95d90c580).html [Accessed on 18 May 2022]

Yadav, M. (2017). Exploring signals for investing in an initial coin offering (ICO), Working paper, Technical University of Berlin

Yi, Z., Luo, Y., Feng, Y., Wang, Y., Feng, Y., & Yang, C. (2022). Research on the Influencing Mechanisms of Backers' Impulsive Support in Reward-Based Crowdfunding Based on Cognitive Appraisal Theory, *Procedia Computer Science*, vol. 199, pp. 423–430