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Signalling in Initial Coin Offerings: The Key Role of Entrepreneurs' Self-efficacy and Media Presence

By analyzing data of more than 1,000 initial coin offerings (ICOs) obtained from seven different ICO information platforms, we investigate the effectiveness of signals used by entrepreneurs to foster ICO funding success. In particular, we examine the effectiveness of venture quality (human capital), level of uncertainty (entrepreneurs' self-efficacy and ambiguity reduction), and level of familiarity among potential investors (media presence). Results imply that media presence and entrepreneurs' self-efficacy are effective signals in the ICO market and thus can increase funding success. Project initiators who communicate (more actively) via social media collect more funds than those who do not. Analogously, entrepreneurs appearing self-efficacious with regard to the quality of their venture receive more funds.

Key words: Crowdsale; Cryptocurrency; Initial coin offering; Signalling; Token sale.

The development of the initial coin offering (ICO) market in recent years highlights its increasing importance for entrepreneurs and investors. Raised funds increased from less than US$0.03 billion in 2015 to more than US$15 billion in the first half of 2018 (EY, 2018). The popularity of ICOs virtually led to a hype among investors. The announcement of an ICO by the traditional photography company Kodak in January 2018,[1] for example, suddenly increased Kodak's popularity among investors. By the end of the announcement day, Kodak's stock price jumped up by about 120%. Hence, the use of an ICO for capital formation seems to be a positive signal for potential investors *per se*. Nevertheless, the success of ICOs varies greatly among different projects: while some ICOs attract several hundred millions of US dollars, many are not able to raise any funds at all.[2] Therefore, investors seem to distinguish between different projects. However,

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[1] See https://kodakone.com/press/detail-page/kodak-and-wenn-digital-partner-to-launch-major-blockchain-initiative-and-cryptocurrency.html

[2] See our summary statistics in Table 1.

given the fact that ICO investors cannot directly observe project quality, ICO projects need to effectively signal venture quality to encourage investors to participate in the token sale.

Surprisingly, a systematic understanding of effective quality signals in the ICO context is still lacking. Therefore, this paper provides theoretical considerations of different quality signals in the context of ICOs and evaluates the effectiveness of different quality signals for ICO funding success. More specifically, we investigate the relevance of venture quality (in terms of human capital), level of uncertainty (in terms of entrepreneurs' self-efficacy and ambiguity reduction), and the level of familiarity (in terms of media presence) for ICO founding amount.

Our study makes a major contribution to research on early-stage financing by providing theoretical considerations and empirical evidence of the effectiveness of various types of signals that are sent out by ICO initiators. A large body of literature has examined the association between information provided by entrepreneurs and investors' funding in different fundraising contexts. Based on signalling theory (Spence, 1973), previous studies provide empirical evidence about which signals are effective in fostering investments of potential investors (Ahlers *et al*., 2015; Ahlstrom and Bruton, 2006; Cosh *et al*., 2009; Kromidha and Li, 2019; Prasad *et al*., 2000). However, the transferability of previously published research on entrepreneurial signalling to ICOs is problematic as every method of capital formation has its own idiosyncrasies (Barbi and Mattioli, 2019; Duffner *et al*., 2009; Giudici *et al*., 2018). Therefore, it is necessary to investigate the capital formation process of ICOs separately.

An ICO can be defined as a crowdsale that takes place on a blockchain. In particular, project initiators generate so-called tokens on a blockchain and then usually sell those tokens to investors in exchange for other established cryptocurrencies such as Ethereum or Bitcoin. Issued tokens grant purchasers a utility of some kind (e.g., access to a future good or service) or a share of a future cash flow generated by the issuing ICO project. In general, the emerging crypto market is characterized by both low regulation and high information asymmetry. While some countries, such as China, have banned ICOs entirely (PBC, 2017), the national legislations of other countries, such as the US and Switzerland, assess token sales on a case-by-case basis (FINMA, 2018; SEC, 2017). Other countries, such as Russia, in turn, seem to foster ICOs by hardly regulating the ICO market at all (MinFin, 2018).

To address our research question, we use data from more than 1,000 ICOs that we identified on seven popular online ICO information platforms.[3] We obtained data on raised funds from those ICO information platforms to assess ICO funding success. Additionally, to avoid potential reverse causality issues, we collected data on human capital, ambiguity reduction, and entrepreneurs' self-efficacy directly from ICOs' white papers that were published before the actual ICO event. Those white papers provide information about the underlying project to potential investors. Moreover, we gather data on the projects' media presence before ICO

[3] More precisely, the most popular ICO platforms are icodata.io, icotracker.net, icobazaar.com, tokendata.io, icobench.com, smithandcrown.com, and icodrops.com.

from eight different social media platforms. Our final sample covers the period from July 2014 to January 2018 and includes an ICO funding volume of approximately US$8.7 billion on aggregate.

Results suggest that both the level of ICOs' media presence and entrepreneurs' self-efficacy are positively related to ICO funding success and thus are effective signals for project quality. More precisely, ICOs that are accompanied by the usage of various social media channels, as well as high social media activity, receive more funds from investors. Second, ICO characteristics that signal entrepreneurs' self-efficacy, such as low bonus granted, high share of tokens retained by the ICO initiators, and short token sale period, are positively related to the ICO funding amount. In contrast, our results do not provide evidence in favour of a clear benefit of projects' human capital and ambiguity reduction in the promotion of ICO funding success.

We apply a test proposed by Oster (2019) on whether the presence of omitted variables could bias our main results. The findings of this test show that our results seem not to be driven by omitted attributes and characteristics of ICOs that are not captured in our main model specification.

INSTITUTIONAL FRAMEWORK

Distributed Ledger Technology, Blockchain, and Initial Coin Offerings

Distributed ledger technology (DLT) is an emerging database concept. Specifically, data are consensually recorded and shared across multiple data stores known as ledgers. As all ledgers have to contain the same data records, new additions to data by members (nodes) of this distributed network are recorded on each ledger, thereby eliminating the need for a central authority (Yu *et al*., 2018). Each independent ledger update is shared in the underlying peer-to-peer network and then, to ensure the validity of a new entry (i.e., to prevent simultaneous transactions on the same asset or to prevent cyber attacks, such as distributed denial-of-service attacks), a consensus algorithm is used. Each distributed ledger network has its predefined cryptographic validation method. Once a consensus is reached, all nodes add this new entry to their ledger. Thus, each node has an identical copy of all the data at any point in time.[4] Moreover, distributed ledgers can be distinguished by two features. First, distributed ledgers are either permissionless or permissioned (Trump *et al*., 2018). While in permissioned networks nodes need a permission from the responsible entity (i.e., the creator of the distributed ledger) to change ledger entries, data updates in permissionless networks are allowed in principle. Second, distributed ledgers can be differentiated concerning access to the network. That is, while anyone can access public ledgers, private ledgers are only accessible by approved nodes.

A blockchain is a specific type of DLT and is the underlying technology used by the vast majority of projects conducting an ICO. A blockchain is characterized by an append-only data structure (i.e., ledgers can only be altered by extension) that

[4] See Natarajan *et al*. (2017) for a more comprehensive description.

exists in the form of a chain of blocks. The key feature of blockchain technology is the implementation of cryptography. Every new addition (block) to the digital ledger that stores information about transactions, for instance information concerning time, money, or transaction partners, is 'hashed' (Natarajan *et al.*, 2017). More specifically, a cryptographic hash function transforms information about transactions to a bit string of fixed size (hash) by applying a mathematical algorithm (Halevi and Krawczyk, 2006). As the hash function is non-invertible, subsequent modifications of the information about transactions result in a different hash and therefore, manipulations are easy to detect. Every block contains the hash of the previous block, information on the considered transaction, and an additional timestamp. As a result, a chain of blocks is formed. Thus, given blocks cannot be altered *ex post* without altering all subsequent blocks of the chain.

Recently, a considerable number of new ventures have employed blockchain technology for capital formation. Known as ICOs, mainly technology startups generate and sell so-called tokens via blockchain in exchange for traditional fiat money or established cryptocurrencies, such as Bitcoin and Ethereum (Roosenboom *et al.*, 2020). More precisely, tokens are entries on a blockchain. ICO initiators determine the token amount, the token value, and other special conditions (e.g., a bonus scheme for early investors). Then, ICO initiators sell the generated tokens in a predetermined ICO period. All terms and conditions, as well as the automatic execution of the token sale, are implemented in so-called smart contracts. More specifically, when an investor transfers money to the ICO project's digital address, that is, the node in a blockchain, they automatically receive an amount of tokens in accordance with the smart contract's terms and conditions. As described above, all transactional data are stored in the underlying blockchain. The creation and sale of tokens take place either on an existing blockchain, such as Ethereum, which is most common for ICOs, or on a new blockchain that is especially created for the ICO.

Distributed tokens usually offer an incentive for investors. According to the type of incentive, there is a distinction between so-called 'utility tokens', 'security tokens', and 'currency tokens' (Ante *et al.*, 2018; Howell *et al.*, 2019). The first represents some form of utility that is granted to token holders, that is, access to future products or services of the ICO project. Typically, only token holders can use the ICO project's future products or services but if the basic features of the services are accessible to everyone, some additional premium features of the services are made exclusively available for token holders. Security tokens, on the other hand, are comparable to stocks or bonds and represent a share of the ICO project or a claim on a future ICO project's cash flows. However, the profit-sharing mechanism lacks a legal basis, which makes it basically impossible for investors to assert any legal claims. Lastly, some tokens neither represent utility nor profit claims, but instead solely function as digital currencies (currency token).

The Process of Initial Coin Offerings

The starting point of a typical ICO is the preparation of a white paper, a document written by the ICO initiators that usually promotes and explains the underlying products or services, introduces the project team, and describes a business plan. It mostly includes token sale characteristics, such as token amount, distributed share of tokens, sale period, possible bonus schemes, as well as a description of how collected funds will be used (Adhami *et al.*, 2018; Chen, 2019).

Simultaneous to the release of a white paper or shortly thereafter, ICO initiators use social media, especially Twitter and BitcoinTalk,[5] to promote their project. The first social media presence constitutes the starting point of a marketing campaign that typically lasts until the end of the token sale period. Usually, marketing activities include almost exclusively activities on social media channels, such as presenting the project's updates, images, and videos, as well as communication with potential investors. Moreover, many initiators introduce their project on ICO information platforms. Typically, all marketing activities of an ICO are limited to online channels.

Many ICO initiators prepend a so-called pre-sale (or pre-ICO) prior to the actual token sale period. The goal of a pre-sale is to attract additional attention from investors, increase the total funding amount, or finance the subsequent main token sale (i.e., technical implementation as well as marketing expenses). Typically, a pre-sale is characterized by very high granted bonuses. After the pre-sale, the main token sale starts and lasts for a predefined period. During this period, the token price usually varies due to a predefined bonus scheme that rewards early investors. Once the token sale period is over and the ICO is successful, ICO initiators begin with the implementation of their project plans as described in the initial white paper. Some successful ICOs strive for a listing of their distributed tokens on a cryptocurrency exchange, such as Binance[6] or Coinbase[7]. Once a token is listed on an exchange, token holders can start trading their tokens on the secondary market. Figure 1 summarizes the typical ICO process.

Legal Framework

With increased public attention, regulators worldwide have started to deal with ICOs and provide regulatory frameworks for token sales. However, the current state of progress of implementation varies by country (Barsan, 2017; Dobrauz-Saldapenna and Klebeck, 2019; Hacker and Thomale, 2018). In particular, regulators have varying views on the legal characterization of cryptocurrencies and tokens, respectively. In consequence of the diverging features of tokens, such as the distinction between utility, security, and currency tokens, some regulators characterize tokens as commodities (Bolotaeva *et al.*, 2019; Enyi and Le, 2017), while others consider them to be property (IRS, 2014). In the following, we give a brief overview of the legislation on ICOs in the five countries with the highest

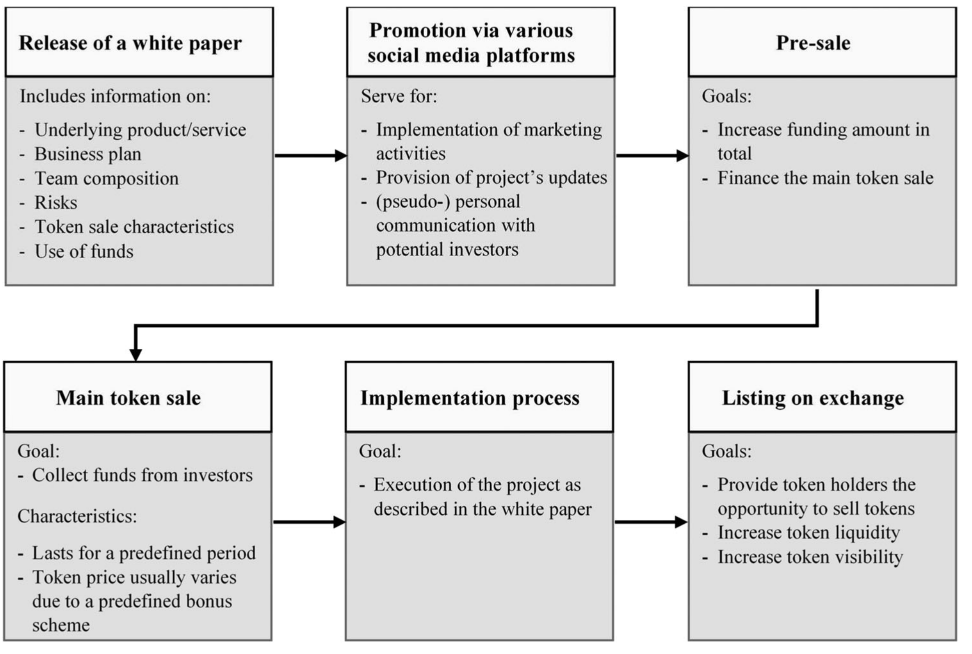
[5] See www.bitcointalk.org

[6] See www.binance.com

[7] See www.coinbase.com

FIGURE 1

SCHEMATIC ICO PROCESS



This figure shows the typical stages of an ICO process.

total amounts raised,[8] that is, the US, the Russian Federation, Switzerland, Singapore, and China.

In the US, legal classification of an ICO is based on the classification of issued tokens. First, the American exchange supervisory authority (SEC) assesses whether an issued token has to be classified as a security. To do so, the SEC applies the Howey test, the standard test for the classification of financial products in the US (Murphy, 1946). According to this test, an issued token has to be classified as a security if the token constitutes a 'contract, transaction or scheme whereby a person invests his money in a common enterprise and is led to expect profits solely from the efforts of the promoter or a third party' (Murphy, 1946, no. 2). In the case of a positive test result, tokens are required to be registered with the SEC and are subject to US security laws (Debler, 2018; Maume and Fromberger, 2019). On the other hand, there is no special regulation of the handling of utility tokens as those are not classified as securities. In summary, US legislation regulates the legality of a token sale on a case-by-case basis (SEC, 2017).

[8] See www.icowatchlist.com/statistics/geo for data on ICO statistics by country.

Analogously to US legislation, for Swiss authorities, the classification of a token constitutes the first step of the assessment for which existing laws are applicable. On 16 February 2018, the Swiss Financial Market Supervisory Authority (FINMA) published guidelines on the regulatory framework for ICOs (FINMA, 2018). According to these guidelines, the FINMA distinguishes between 'payment tokens', 'utility tokens', and 'asset tokens'. Only asset tokens that 'represent assets such as a debt or equity claim on the issuer' (FINMA, 2018, p. 3) are treated as securities and therefore, are subject to security laws.

In Russia, the central bank of the Russian Federation is responsible for the regulation of ICOs. In January 2018, the Ministry of Finances published the first draft of a law regulating digital financial assets, called the Digital Assets Regulation Bill (MinFin, 2018). In accordance with this draft, tokens should be classified as property. Another feature of this draft is that qualified investors can unrestrictedly participate in ICOs while retail investors have only a restricted right to participate.[9] Although there have been several other drafts since then, as of the end of March 2020, there is still no special regulation for token sales in Russia, that is, Russian authorities do not regulate ICOs at all (Partz, 2020).

The Singaporean regulatory authority (MAS), on 1 August 2017, issued guidance on how they will regulate issued tokens that fall under the Securities and Futures Act (SFA) (MAS, 2017b). In this statement, the MAS announced that it would apply existing security laws if a token falls within the definition of a security. Also in 2017, the MAS warned investors against investing in ICOs due to fraudulent conduct by a high number of ICO initiators (MAS, 2017a). In summary, regulation of ICOs is also based on a case-by-case assessment by Singaporean authorities.

In China, seven central government regulators issued an announcement on 4 September 2017 wherein they prohibited ICOs entirely to protect Chinese investors from fraudulent conduct by ICO initiators (Deng *et al.*, 2018; PBC, 2017). Until then, Chinese regulators did not regulate ICOs at all.

Overall, the legal characterization and regulation of token sales vary markedly for the individual countries. While some countries, such as China and South Korea, take a very restrictive approach by entirely prohibiting ICOs, other countries, such as Russia, do not regulate ICOs at all. Consequently, regulation significantly influences the regional distribution of conducted ICOs.

Market Overview

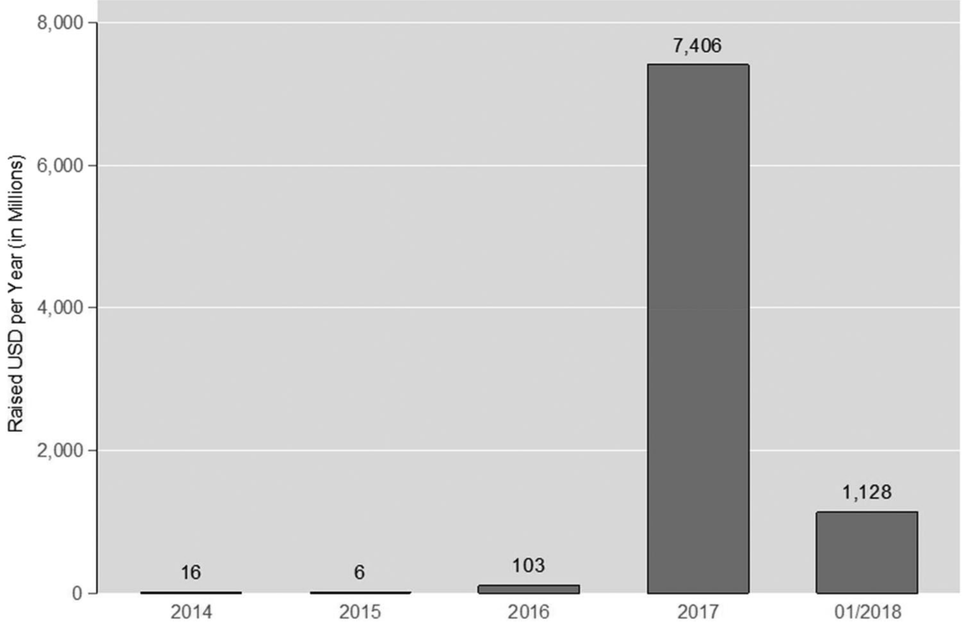
Figure 2 provides an overview of the development of the ICO market for our sample from July 2014 to January 2018. Presented numbers are in line with other public sources, such as the research report by the accounting firm Ernst & Young (2017).

After a total amount of about US$125 million from 2014 to 2016, ICOs collected more than US$7 billion in 2017 and more than US$1 billion in the first month of 2018, and thus constitute a fast-growing funding source in global financial markets.

[9] If necessary, Russian authorities reserve the right to prohibit a token sale on a case-by-case basis.

FIGURE 2

DEVELOPMENT OF THE ICO MARKET FROM JULY 2014 TO JANUARY 2018



This figure features all ICO proceeds for our sample comprising ICOs that were conducted between July 2014 and January 2018. The bars illustrate all proceeds in the respective periods indicated below.

The global ICO market is characterized by a wide geographical dispersion. Figure 3 presents the distribution of ICO projects' origin for our underlying data sample.

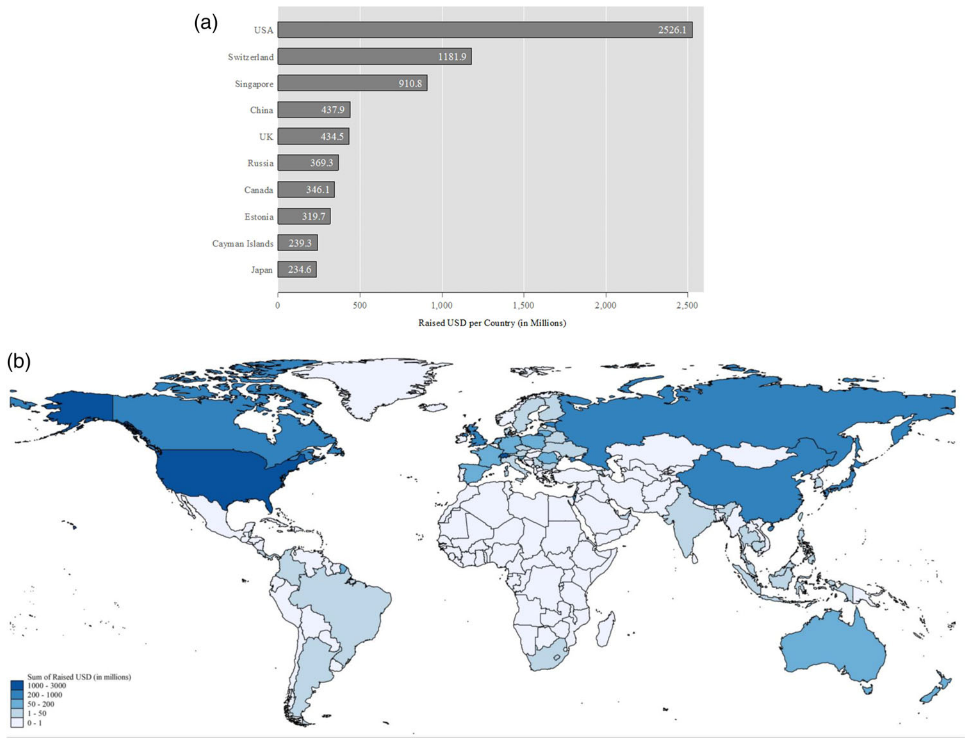
As can be seen from Figure 3, besides Western countries, such as the US, the UK, and Switzerland, Asian countries and Russia also play an essential role in the ICO market. Moreover, ICOs are popular in offshore financial centres, such as the Cayman Islands. In addition to legal and regulatory reasons, this could be an indication that many ICOs are conducted for reasons of tax avoidance, money laundering, or other fraudulent intentions (Tiwari *et al.*, 2020). A study prepared by the ICO advisory firm Statis Group reports that about 11% of ICO investments fell prey to fraudulent projects ('scams') (Dowlat, 2018). Huang *et al.* (2019) provide a more detailed overview of the geography of ICOs.

Comparison of ICOs with Conventional Crowdfunding

As stated above, an ICO can be defined as a form of early-stage financing that uses distributed ledger technology, which, depending on the token form, grants monetary or non-monetary rewards to the backers. The forms of conventional capital formation closest to ICOs are reward-based and equity-based

FIGURE 3

RELEVANCE OF ICO PROJECTS' COUNTRIES OF ORIGIN ACCORDING TO RAISED FUNDS



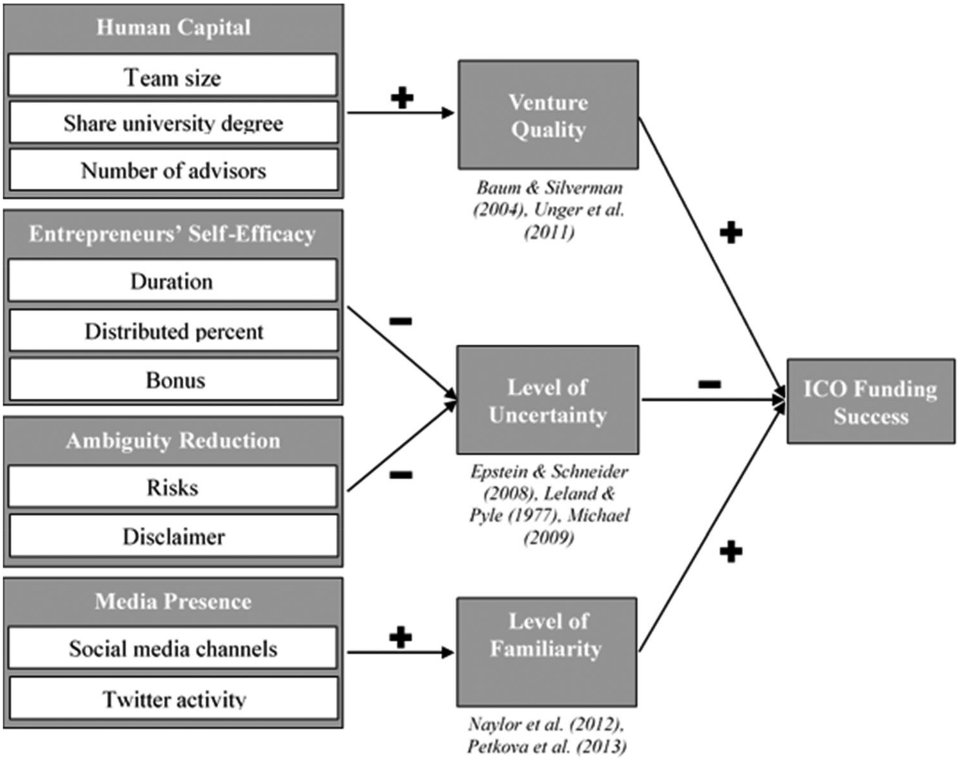
Panel A shows the top 10 leading countries worldwide by value of funds raised through ICOs in the period July 2014 to January 2018. Panel B presents the geographical dispersion of ICO projects on the basis of total funds raised in the period from 2015 to January 2018.

crowdfunding. As defined by Belleflamme *et al.* (2014, p. 588), 'Crowdfunding involves an open call, mostly through the Internet, for the provision of financial resources'. In reward-based crowdfunding, capital-seeking projects provide backers with non-monetary rewards or products in exchange for funding (Ahlers *et al.*, 2015). Accordingly, ICOs issuing utility tokens can be considered as a form of reward-based crowdfunding. On the other hand, in equity-based crowdfunding, funders receive an amount of equity or bond-like shares in the underlying project (Ahlers *et al.*, 2015). Under this definition, ICOs issuing security tokens can be regarded as a form of equity-based crowdfunding.

Nevertheless, ICOs and conventional crowdfunding campaigns differ in various aspects. In general, in conventional crowdfunding the investment process is centralized on crowdfunding platforms that act as intermediaries (Belleflamme

FIGURE 4

HYPOTHESIZED MODEL



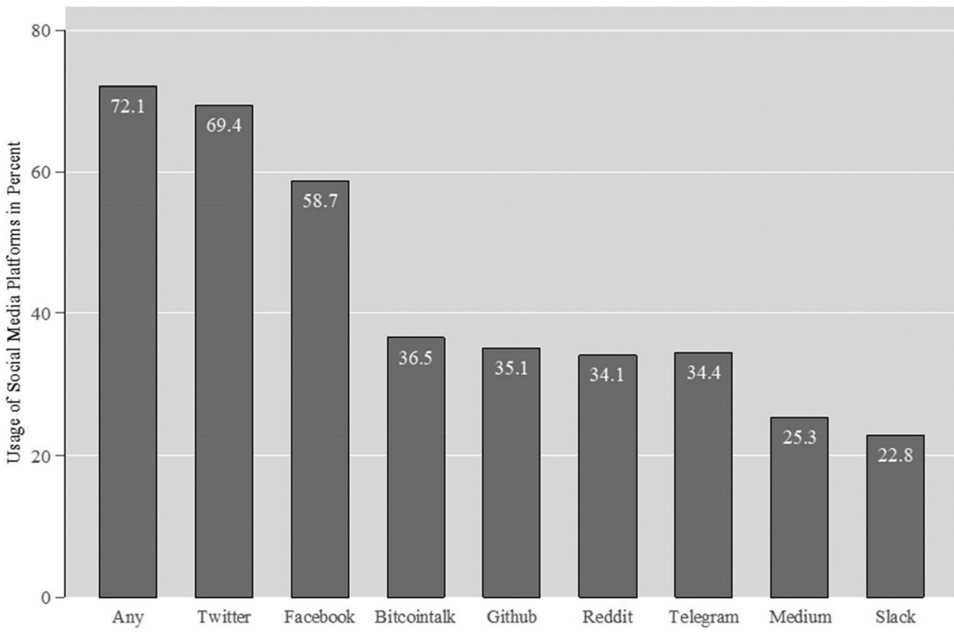
This figure illustrates hypothesized determinants of funding success.

et al., 2014). Since crowdfunding platform services are mostly directed at domestic investors and projects, the investor base in crowdfunding has a local character (Giudici *et al*., 2018). Moreover, reward-based crowdfunding is often characterized by social ties between investors and fundraisers (Giudici *et al*., 2018). In ICOs, however, using the DLT, investors allocate their financial resources directly to the project initiators. Consequently, project initiators and investors do not depend on any (local) intermediary platform. Therefore, given a particular project, we assume a wider geographical dispersion of ICO investors compared to crowdfunding investors.

With regard to the typology of fundraisers, ICOs and conventional crowdfunding are similar. More specifically, startups and young companies usually make use of conventional crowdfunding, that is, equity-based and reward-based crowdfunding, to foster the growth of their venture (Paschen, 2017). Although some established companies conduct ICOs, the majority of ICO projects are at an early stage.

FIGURE 5

USAGE OF SOCIAL MEDIA PLATFORMS BY ICO PROJECTS IN PERCENT



This figure shows the percentage of ICO projects that use the respective social media platform. The first bar includes all ICO projects that use at least one social media platform.

According to the differences in the typology of investors and fundraisers, there are great disparities in terms of number of campaigns and average funding per campaign. As stated above, ICO initiators collected more than US$7 billion in 2017, which constitutes a value similar to the transaction value of equity-based and reward-based crowdfunding campaigns taken together (Statista, 2019a, 2019b). However, while less than 1,000 ICO campaigns are responsible for this high transaction value in the emerging crypto market, the transaction value in the conventional crowdfunding market is generated by about 38,000 equity-based crowdfunding campaigns and about 5.2 million reward-based crowdfunding campaigns (Statista, 2019c, 2019d). As a result, the average ICO campaign from our sample collected about US$8.6 million, whereas equity-based crowdfunding campaigns and reward-based crowdfunding campaigns collected US$78,867 and US$765 on average, respectively.

A consideration of the geographical distribution of ICO projects and conventional crowdfunding campaigns reveals differences as well. With regard to reward-based crowdfunding, about 80% of total funds were collected in China, while another 10% were collected in the US (Statista, 2019a, 2019b). These numbers suggest a high level of market concentration. In equity crowdfunding, China and the US constitute the most important markets. However, as campaigns in China account for about 21% of the market volume and campaigns in the US account for about 17%, the level of market concentration is essentially lower. With regard to the regional distribution of ICOs as presented in Figure 3, the leading role of the US becomes apparent. The US accounts for about 29% of total funds in our sample. Furthermore, while the Swiss and the Singaporean market globally play a key role, the Chinese market is less important. However, in contrast to conventional crowdfunding that, according to Li (2016), is scarcely regulated in China, ICOs were entirely banned in 2017 (PBC, 2017). In summary, apart from the availability of financial resources, the geographical distribution of ICOs and conventional crowdfunding campaigns are mainly driven by different countries' regulatory requirements.

THEORETICAL BACKGROUND AND HYPOTHESES

Determinants of ICO Funding Success

Like any other investment in new ventures, ICO investments are subject to the well-documented principal–agent problem (Fama and Jensen, 1983; Jensen and Meckling, 1976; Van Osnabrugge, 2000). On the one hand, investors (principals) try to select the best investment from the given options. On the other hand, entrepreneurs or project representatives (agents) aim to attract funds from investors. However, this allocation process is characterized by information asymmetry. Agents usually have more information about the true value of a project than principals. The low level of legal clarity combined with the anonymity of participants in the DLT, as described in the previous chapter, means that information asymmetry is eminently high for ICOs compared to conventional start-up financing (Momtaz, 2020). Nevertheless, ICO investors, like other investors, seek to reduce the likelihood of investing in 'lemons' (Akerlof, 1970). Hence, to attract funds from investors, project representatives have to decrease the information asymmetry perceived by potential investors. Therefore, according to signalling theory (Spence, 1973), project representatives need to provide information to investors to signal project quality. However, not every type of information is an effective quality signal (Ahlers *et al.*, 2015). Effective signals are characterized as observable, that is, investors recognize and understand them, and costly, that is, the production of these signals entails costs (Connelly *et al.*, 2011).

From a theoretical point of view and based on previous literature, we develop a framework for what types of information constitute effective signals that are used by entrepreneurs to convince potential investors and thus foster funding success. We argue that there are three channels related to funding success within the ICO context: (1) venture quality; (2) level of uncertainty; and (3) level of familiarity. Figure 4 shows the hypothesized model.

First, it is well-established that investors are more likely to invest in projects where the observable characteristics suggest higher venture quality and therefore higher future returns (Ahlers *et al.*, 2015; Baum and Silverman, 2004). Since the majority of ICO projects are at an early stage of the business, they cannot provide unambiguous performance measures. Therefore, potential investors need to look for alternative proxies of venture quality (Ahlers *et al*., 2015; Baum and Silverman, 2004; Podolny, 1993). Based on Ahlers *et al*. (2015) and Baum and Silverman (2004), we identify three proxies of venture quality, namely human capital, social capital, and intellectual capital. We summarize these proxies under the term 'human capital'.

The second channel that is related to funding success is the level of uncertainty. More specifically, assuming that people prefer known risks over unknown risks (Ellsberg, 1961) potential investors are more likely to invest in ventures that provide more unambiguous information, especially in a market characterized by high information asymmetry (Leland and Pyle, 1977). We argue that there are two options to provide more unambiguous information and thus lower the level of uncertainty in the ICO context. First, entrepreneurs can show high self-efficacy by setting ICO parameters that are unambiguous, such as bonuses, duration, and share of distributed tokens, in a way that suggests conviction in their own venture (*entrepreneurs' self-efficacy*). For instance, by specifying a short ICO period, an entrepreneur signals that they are convinced that the quality of the ICO project is so high that potential investors are also aware of it, resulting in sufficient financing within a short period. At the same time, by shortening the ICO period, the entrepreneur may forgo higher financing. Thus, setting those parameters constitutes both an observable and costly signal that reduces the ambiguity level among potential investors. Second, in the context of ICOs, it is possible for entrepreneurs to provide detailed information on potential risks and legal issues within the ICO white paper (*ambiguity reduction*). Providing this type of information reflects entrepreneurs' outlook (Michael, 2009) and enables potential investors to base their investment decisions on this information (Epstein and Schneider, 2008).

The third channel is based on literature providing evidence that consumers increasingly use social media to learn about unfamiliar brands (Heller Baird and Parasnis, 2011; Naylor *et al*., 2012). Accordingly, diverse and intense communication by entrepreneurs triggers both familiarity among potential investors and media attention (Petkova *et al*., 2013). Consequently, funding success is more likely for projects that communicate actively because higher familiarity and attention are related to higher funding amounts (Aggarwal *et al*., 2012; Petkova *et al*., 2013). As ICO projects mainly use social media to communicate with their potential investors, we argue that both the diversity (number of social media platforms) and the intensity of social media communication (Twitter activity) improve funding success.

Human Capital

Every new venture starts with a team of entrepreneurs that identifies a business opportunity and tries to exploit it (Shane and Venkataraman, 2000; Venkataraman, 1997). Therefore, it is evident that the human capital, that is, all the knowledge, talents, skills, abilities, experience, intelligence, judgement, and wisdom of the project team (Haq, 1996) is an important factor in the success of every entrepreneurial project. Unsurprisingly then, a considerable amount of empirical literature has emphasized the importance of human capital for venture success (Bates, 1990; Baum and Silverman, 2004; Ray and Singh, 1980; Unger *et al*., 2011). Therefore, it is likely that potential investors are also aware of this relationship. Venture capitalists, for example, use firms' team characteristics as one of the most important criteria for their investment decisions (Zacharakis and Meyer, 2000). Analogously, Ahlers *et al*. (2015) and Baum and Silverman (2004) demonstrate that human capital is an effective signal in conventional crowdfunding. Both social capital, that is, social networks and thus access to valuable information, as well as intellectual capital, that is, employee expertise, are integral parts of human capital. Since ICO projects, like conventional crowdfunding projects, are usually at an early stage of the business lifecycle, human capital is an important factor for project success. Consequently, we argue that human capital is an effective signal of venture quality for potential investors and thus, positively relates to ICO funding success.

H1: Human capital positively relates to ICO funding success.

Entrepreneurs' Self-efficacy

In addition to the skills and knowledge of the team members, starting a new venture also requires the entrepreneur's belief that the project will succeed. Dimov (2010) shows that opportunity confidence is an important factor in venture emergence. Opportunity confidence describes the personal belief of an entrepreneur that an opportunity is feasible and that they are able to establish a venture that exploits this opportunity. If entrepreneurs believe that their actions can produce the desired results, they have an incentive to start a venture. This trait is termed 'self-efficacy' (Bandura, 2010). In this context, Baum and Locke (2004) find that entrepreneurs' self-efficacy is positively related to subsequent venture growth. The authors show that self-efficient entrepreneurs also have a higher passion for the business. In the context of ICOs, entrepreneurs can show high self-efficacy by setting ICO parameters that are unambiguous, such as low bonuses, short duration, and low share of distributed tokens (i.e., a higher share of tokens remains for the entrepreneurs). This observable and costly behaviour shows entrepreneurs' conviction in their own venture and might be an effective signal of venture quality that reduces the level of uncertainty from the investors' point of view. Since people prefer known risks over unknown risks (Ellsberg, 1961), we assume that entrepreneurs' self-efficacy is related to higher funding amounts. We hypothesize:

H2: Entrepreneurs' self-efficacy positively affects ICO funding success.

Ambiguity Reduction

Ambiguity aversion (Ellsberg, 1961) is when individuals prefer known risks over unknown risks. In the case of investments, the implication is that investors prefer an investment opportunity for which they know all underlying risks and probabilities to an equivalent investment opportunity with ambiguous information (Park and Patel, 2015). Ahlers *et al*. (2015) find that in the case of conventional crowdfunding, providing detailed information about risks can be an effective signal and therefore, fosters funding success. Given the low level of legal clarity in the ICO environment, we expect that potential investors are even more sensitive to the level of ambiguity linked to the ICO project. We argue that reducing ambiguity regarding the ICO project signals the team's awareness of potential risk factors as well as its preparedness for potential consequences. Additionally, potential investors have a better basis on which to form expectations, which is preferred by investors (Epstein and Schneider, 2008). Transferring the idea of ambiguity aversion to the ICO context, we argue that if the level of uncertainty decreases, investors' likelihood to invest increases. Therefore, we hypothesize:

H3: Reducing ambiguity regarding the ICO project positively affects ICO funding success.

Level of Media Presence

In traditional entrepreneurial financing, such as venture capital or angel investment, personal communication is a key factor in establishing social relationships between entrepreneurs and investors to decrease perceived information asymmetries and to signal project quality (Kollmann and Kuckertz, 2006; Shane and Cable, 2002). ICOs, however, like conventional crowdfunding, take place online. Consequently, most direct personal communication is mainly replaced by pseudo personal communication via social media (Drobetz *et al*., 2019; Moritz *et al*., 2015). Projects that show a higher (social) media presence are more likely to become familiar to potential investors (Heller Baird and Parasnis, 2011; Naylor *et al*., 2012). Moreover, active use of social media demonstrates preparedness and thus signals venture quality (Courtney *et al*., 2017). Additionally, increasing social media activity can enhance the salience of an ICO and thus possibly help to inform investors about the upcoming investment opportunity (Solomon, 2012; Sprenger *et al*., 2014). Empirical literature also supports the hypothesis of media presence as an effective signal by finding that the use of media is positively related to crowdfunding success (Beier and Wagner, 2015; Courtney *et al*., 2017). Additionally, intense and diverse social media communication might increase the attention an ICO project receives from different types of traditional media, which is related to higher funding amounts (Petkova *et al*., 2013). Therefore, we hypothesize:

H4: The level of media presence positively affects funding success.

DATA SET AND CONSTRUCTION OF VARIABLES

Data Sources and Sample Construction

We obtain our data from three different sources: ICO information platforms, ICO white papers, and ICO projects' social media channels. First, we collected data from seven different ICO information platforms[10] to define our sample and to derive our dependent variable, that is, raised funds. Second, we used information from the ICO white papers to create the majority of our independent variables. Third, we investigated the presence of each ICO project on eight different social media platforms. We also investigated ICOs' Twitter accounts more deeply to assess the social media activity of ICOs. (Please see Appendix A for a detailed description of the data processing procedure.)

Online ICO information platforms are public databases that contain information about upcoming, current, and past ICOs. Therefore, those platforms are the starting point for our data collection. Typically, these platforms contain information on the name of the ICO, the ICO's time schedule, details about the offering, but also links to the project's website, white paper, or social media channels. After the token sale event, most platforms also list the funds raised by the ICO. However, an entry in those platforms is not mandatory. As a result, no platform contains complete information about all ICOs that have taken place. Therefore, and to get an initial sample that is as comprehensive as possible, we collect data from seven different ICO information platforms from July 2014 to January 2018. We manually match the data from the seven different ICO information platforms and remove duplicates. We highlight the importance of a manual merging procedure, as the names of the projects often slightly differ among the different platforms. Next, we remove ICO pre-sales from our sample, as we are only interested in ICO main sales. This procedure results in a sample of 1,057 different ICOs.

After defining our sample, we collect data to generate variables to proxy for ICO funding success as well as for the different signals within the ICO context. We use the data from the different ICO platforms to obtain values for our dependent variable. As mentioned above, ICO information platforms offer comprehensive data about the ICOs besides the collected funds. However, we are not able to obtain a time stamp for the data entries. To avoid potential reverse causality issues, we therefore collect our data on the explanatory variables from sources other than the ICO information platforms. ICOs' white papers are our first source of data for our explanatory variables. White papers are documents written by ICO initiators to promote and explain their products or services as well as to present the project team and the planned ICO schedule to potential investors. As those white papers offer a creation date, we can base our investigation on information that was available to investors before the actual ICO period. From those white papers, we obtain data regarding the projects' human capital, entrepreneurs' self-efficacy, ambiguity reduction, as well as our control variables.

[10] We use the platforms icodata.io, icotracker.net, icobazaar.com, tokendata.io, icobench.com, smithandcrown.com, and icodrops.com.

The second source of data for our explanatory variables are social media platforms. More precisely, we use data from social media platforms to proxy for the level of media presence of each ICO project. Therefore, we first scan eight different social media platforms, namely Twitter, Facebook, Bitcointalk, Github, Reddit, Telegram, Medium, and Slack, for accounts of each ICO project that have been set up before an ICO. Moreover, we assess the activity of each ICO project on Twitter before the main token sale event.

Measure of ICO Funding Success

In the context of entrepreneurship and early-stage financing, success is not a clearly defined concept. Thus, studies use diverse approaches to capture funding success (e.g., Ahlers *et al*., 2015; Ahlstrom and Bruton, 2006; Courtney *et al*., 2017). As we try to capture funding success from the ICO initiators' perspective we use collected funds during the token sale event as our dependent variable. The more funds an ICO project collects, the more successful is the ICO.

Another way to assess early-stage investment success is to investigate if there will be a successful exit (e.g., an initial public offering or a private placement) in the future. However, this method describes success from the investors' view, while we are interested in capturing success from the ICO initiators' perspective. Furthermore, we lack information on whether an ICO campaign is even considering an exit in the (near) future. Therefore, we focus our investigation on the ICO event itself instead of a potential exit event in the future.

A further option is to define success in relation to the funding goal. Subsequently, some researchers measure success with a binary variable equal to one if the funding target has been reached and zero otherwise (Courtney *et al*., 2017; Wang *et al*., 2018), or with a metric variable that captures the funds actually collected in proportion to the funding goal (Duffner *et al*., 2009). Most ICOs, however, do not define an explicit funding goal (Fisch, 2019). Frequently, ICOs only disclose a so-called 'soft cap' or a 'hard cap'. The soft cap describes a threshold that, if not reached during the ICO, usually leads to a complete refund of all ICO investments. As ICO initiators try to avoid such an event, they often set the soft cap to an especially low level. The hard cap, on the other hand, defines the maximum amount of total investment approved by the algorithm of the ICO's smart contract. Hence, the hard cap level often does not relate to the funds needed for the accomplishment of the underlying project. Therefore, the soft cap and the hard cap are not usually adequate benchmarks for ICO funding success.

Construction of Explanatory Variables

We collected data for six different categories of variables: (1) funding success; (2) human capital; (3) entrepreneurs' self-efficacy; (4) ambiguity reduction; (5) level of media presence; and (6) controls. We use the following variables for our estimations.

As discussed in the previous section, we define ICO success as the funds collected by a project during the token sale event. Therefore, the dependent variable in our model is the amount raised by the project during the ICO main sale in millions of US dollars (*raised mUSD)*.

Our first category of explanatory variables captures human capital. Following the literature on conventional crowdfunding (Ahlers *et al.*, 2015), we extract the size of the project team (*team size*) as well as the share of team members that hold a university degree (*share university degrees*) to proxy for human capital. Moreover, we argue that projects' advisors can offer the team valuable guidance as well as access to a personal business network, thus improving human capital (social capital) as well. Therefore, we use the projects' number of advisors (*number advisors*) as a third proxy for human capital.

To proxy for entrepreneurs' self-efficacy, we obtain data about ICO duration (*duration*), the share of tokens distributed to the public during the ICO (*distributed percent*), and the potential bonuses (*bonus*) from the projects' white papers. We argue that a short ICO duration (set prior to the token sale event), such as in the case of equity crowdfunding (Lukkarinen *et al.*, 2016), signals the project team's confidence in their ability to collect the needed funds in a short period and, therefore, can serve as a proxy for entrepreneurs' self-efficacy. Moreover, we argue that the higher the share of tokens that remains in the ownership of the project team, the higher the team's confidence in project success (Ahlers *et al.*, 2015). It follows that the lower the share of tokens distributed to the public, the higher the team's self-efficacy. This is in line with the literature documenting that entrepreneurs with a higher self-efficacy hold larger stakes in their venture (Cassar and Friedman, 2009). Lastly, we argue that the lower the potential discounts or bonuses in an ICO that initiators offer to investors, the higher the project team's confidence in the project's quality. Accordingly, setting those ICO parameters in the described manner reduces the level of uncertainty from the investors' point of view.

Our third category of explanatory variables comprises proxies for ambiguity reduction. Some white papers offer a disclaimer containing legal information about the ICO (investment). Moreover, a decent number of white papers offer a section about potential risk factors linked to participation in the ICO. In this context, Arnold *et al.* (2010) as well as Park and Patel (2015) show that there is a relationship between the ambiguity of a project perceived by investors and the risk factors' section in the underlying IPO prospectus. Therefore, we use a dummy variable that captures the existence of a section regarding potential risk factors (*risk factors*) in the ICO's white paper as a proxy for ambiguity reduction. Additionally, we include a second dummy variable equalling one if there is a legal disclaimer (*disclaimer*) in the corresponding white paper, and zero otherwise.

As explained above, we use data from eight different social media platforms to assess the level of media presence of a project. Therefore, we count the number of social media channels a project uses before ICO. The resulting variable (*social count*) is a proxy for the diversity of communication and our first measure of the level of media presence of a project.

Figure 5 gives an overview of the usage of the different social media platforms among the projects in our sample. More than 72% of ICOs use at least one social

TABLE 1

SUMMARY STATISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	N	Mean	SD	Min.	p5	p25	p50	p75	p95	Max
Panel A: ICO success										
raised mUSD	1,057	8.64	20.59	0	0	0	0.89	9.75	37.86	258.00
Panel B: Human capital										
team size	863	4.47	5.91	0	0	0	3	7	14	80
share university degree	863	0.14	0.27	0	0	0	0	0.17	0.88	1.00
number advisors	863	1.81	3.56	0	0	0	0	3	10	35
Panel C: Entrepreneurs' self-efficacy										
duration	830	34.48	26.48	1	1	17	31	45	91	195
distributed percent	809	0.61	0.25	0.00	0.15	0.45	0.62	0.80	1.00	1.00
bonus	779	0.25	0.59	0.00	0.00	0.00	0.15	0.30	0.875	10.00
Panel D: Ambiguity reduction										
risks	863	0.22	0.42	0	0	0	0	0	1	1
disclaimer	863	0.34	0.47	0	0	0	0	1	1	1
Panel E: Media presence										
social count	1,057	3.16	2.48	0	0	0	3	5	7	8
Twitter activity	734	64.30	106.43	0	0	0	29	81	258	1,087
Panel F: Controls										
token price	776	15.66	288.16	0.00	0.01	0.10	0.30	1.00	10.00	7,912.60
pre-sale	863	0.52	0.50	0	0	0	1	1	1	1
goal mUSD	774	29.79	46.63	0.03	0.50	4.50	15.01	35.00	100.00	500.00

This table contains the summary statistics of our dataset. We define the variables as follows: *raised mUSD* is the amount raised by the project during the ICO main sale in millions of US dollars; *team size* is the number of members in the project team; *share university degree* is the share of the team members that hold a university degree; *number advisors* is the number of advisors in the ICO project; *duration* is the duration of the ICO in days; *distributed percent* is the share of tokens distributed to the public during the ICO; *bonus* is the maximum bonus granted to investors during the ICO; *risks* is a dummy variable that equals one if there is a section in the ICO white paper that declares potential risk factors of the ICO (investment), and zero otherwise; *disclaimer* is a dummy variable that equals one if there is a (legal) disclaimer in the ICO white paper, and zero otherwise; *social count* is the number of social media platforms the ICO project uses; *Twitter activity* is the number of tweets the ICO project posted in the 60 days before the start of the ICO; *token price* is the price of the token during the ICO in US dollars; *pre-sale* is a dummy variable that equals one if there was a pre-sale before the ICO main sale; *goal mUSD* is the fundraising goal of the ICO project in US dollars.

media channel. Among the eight different channels, Twitter is the most prominent. Considering all projects that use at least one social media channel, more than 96% use Twitter.

In addition to the number of social media platforms, the activity on those platforms is an important factor for the overall media presence of an ICO project. As Twitter is the most common social media channel among ICO projects, we identify the number of posts for each ICO project on Twitter in the last 60 days before the ICO as a second measure of media presence (*Twitter activity*).

Further controls constitute the last category of variables. Our control variables are the token price during ICO (*token price*), the projects' funding goal (*goal mUSD*), and a dummy variable for the existence of a pre-sale before ICO (*pre-sale*).

Table 2

CORRELATION MATRIX

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
raised mUSD (1)	1													
team size (2)	0.125***	1												
	(0.000)													
share university degree (3)	0.029	0.302***	1											
	(0.335)	(0.000)												
number advisors (4)	0.109***	0.526***	0.299***	1										
	(0.000)	(0.000)	(0.000)											
duration (5)	–0.179***	–0.049	0.015	–0.021	1									
	(0.000)	(0.108)	(0.613)	(0.486)										
distributed percent (6)	–0.174***	–0.041	–0.056**	–0.088***	0.054*	1								
	(0.000)	(0.151)	(0.046)	(0.002)	(0.099)									
bonus (7)	–0.076**	–0.078***	–0.056**	–0.059**	0.055	0.003	1							
	(0.028)	(0.006)	(0.049)	(0.036)	(0.101)	(0.927)								
disclaimer (8)	0.047	0.150***	0.091***	0.190***	0.008	–0.042	–0.001	1						
	(0.166)	(0.000)	(0.007)	(0.000)	(0.824)	(0.226)	(0.982)							
risks (9)	–0.006	0.161***	0.115***	0.165***	–0.002	0.027	–0.023	0.388***	1					
	(0.858)	(0.000)	(0.001)	(0.000)	(0.948)	(0.437)	(0.522)	(0.000)						
social count (10)	0.253***	0.188***	0.068***	0.197***	–0.135***	–0.049*	–0.010	0.087**	0.059*	1				
	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.087)	(0.724)	(0.011)	(0.083)					
Twitter activity (11)	0.111***	0.213***	0.114***	0.203***	–0.051	–0.040	–0.060*	0.009	0.079**	0.105***	1			
	(0.003)	(0.000)	(0.000)	(0.000)	(0.162)	(0.216)	(0.067)	(0.823)	(0.046)	(0.001)				
token price (12)	–0.008	–0.035	–0.023	–0.025	–0.033	0.041	0.011	–0.034	–0.020	0.000	0.009	1		
	(0.804)	(0.284)	(0.473)	(0.450)	(0.322)	(0.222)	(0.758)	(0.348)	(0.572)	(0.994)	(0.803)			
pre-sale (13)	0.057*	0.376***	0.277***	0.273***	–0.003	–0.057**	–0.078***	0.171***	0.056*	0.157***	0.145***	–0.035	1	
	(0.061)	(0.000)	(0.000)	(0.000)	(0.922)	(0.044)	(0.006)	(0.000)	(0.095)	(0.000)	(0.000)	(0.281)		
goal mUSD (14)	0.174***	0.009	–0.049	0.018	0.046	0.000	0.048	–0.007	–0.018	–0.012	0.008	–0.013	0.014	1
	(0.000)	(0.774)	(0.125)	(0.572)	(0.172)	(0.996)	(0.167)	(0.853)	(0.620)	(0.708)	(0.831)	(0.700)	(0.659)	

This table shows the Pearson correlation coefficients for *raised mUSD* and all explanatory variables used in our main regressions. *p*-values are given in parentheses below the coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3

MEDIAN SPLIT OF RAISED MUSD

VARIABLES	Number of observations	Raised mUSD Below median group (B)	Above median group (A)	Difference(A) – (B)	*t*-statistic
Human capital					
team size	664	3.720	6.295	2.575	5.366***
share university degree	664	0.145	0.165	0.0206	0.956
number advisors	664	1.241	2.810	1.569	5.564***
Self-efficacy					
duration	664	41.430	26.270	–15.160	–7.605***
distributed percent	664	0.657	0.585	–0.072	–3.977***
bonus	664	0.343	0.178	–0.165	–3.454***
Ambiguity reduction					
disclaimer	664	0.352	0.392	0.039	1.043
risks	664	0.229	0.268	0.039	1.167
Media presence					
social count	664	2.732	4.669	1.937	11.38***
Twitter activity	521	35.000	63.870	28.870	4.201***
Additional controls					
token price	664	9.640	26.290	16.650	0.688
pre-sale	664	0.584	0.557	–0.027	–0.705
goal mUSD	664	26.620	30.560	3.935	1.253

This table presents a comparison of the means of our explanatory variables for the two subsamples resulting from a median split according to *raised mUSD*. Variables are as defined in Table 1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The token price is the price (i.e., the amount of traditional fiat money or established cryptocurrencies) an investor has to pay for one token of the ICO in US dollars. Often the token price is stated in Ethereum or Bitcoin and, therefore, the US dollar token price varies over time due to the significant fluctuations of these cryptocurrencies. In those cases, we identify the average US dollar token price during the ICO period.

A further control variable is the funding goal. However, as mentioned previously, project initiators often define no concrete funding goal. Mostly, only the so-called hard cap is given. Nevertheless, following the literature on conventional crowdfunding (Ahlers *et al*., 2015; Courtney *et al*., 2017), we control for the stated funding goal, soft cap, or hard cap (depending on availability) in US dollars (*goal mUSD*) but point out that the reliability of this control variable is relatively small.[11]

[11] Only 43 of the projects provided a specific funding goal. Moreover, 95 projects provided a soft cap. Other projects either provided a hard cap or no information about a funding goal at all. Therefore, we create the variable *goal mUSD* as follows. If the project provides a specific funding goal the variable equals that goal. Moreover, if the project provides no funding goal, the variable equals the soft cap. If the project provides neither a funding goal nor a soft cap, the variable equals the hard cap. For reasons of robustness, we test whether our results are affected by the construction of the variable. However, results do not change significantly. Additionally, adding interaction terms for the respective goal types does not change our results. Regression results are available upon request.

Lastly, we identify whether a project offers a pre-sale before the ICO main sale. We do so because such projects could be more familiar to investors. The resulting variable (*pre-sale)* is a dummy variable that equals one if there was a pre-sale before the ICO, and zero otherwise.

Summary Statistics and Correlations

Table 1 provides the summary statistics for our sample. It contains six panels (A to F). Note that we have 1,057 observations for our variables *raised mUSD* and *social count* as we obtained the data for those variables from ICO information platforms and social media platforms, respectively. Other variables (apart from *Twitter activity*), however, are obtained from the projects' white papers. Hence, these data are only available for ICOs providing a white paper before the token sale event. As only about 82% of the projects in our sample provided a white paper, the maximum number of observations for those variables is 863. The variable *Twitter activity* holds only 734 observations, as it is only available for projects that had a Twitter account pre ICO.

As can be seen in Panel A, ICO projects raised US$8.64 million on average. The median, however, is only US$893,000 indicating a positively skewed distribution of *raised mUSD*.[12] More than 25% of the ICOs collected no funds at all. It follows that, despite the high popularity of ICOs, investors did not blindly delegate money to every project that was somehow related to distributed ledger technology. The maximum raised funds by one project in our sample was US$258 million by the Hdac project. While some news articles report ICOs that raised much higher sums (Kharif, 2018), the relatively low value in our sample results from the fact that we restricted our sample to ICOs that were completed until January 2018.[13]

Panel B provides data about the human capital of ICO projects. The average stated team size is four, while 14% of the team members declare having a university degree. Moreover, ICO projects in our sample present two advisors on average. More than 25% of ICOs do not present any founders or team members in their white papers.

Panel C shows that the mean of ICO duration is about 34 days. However, there are also ICOs that take place on only one day or that take up to 195 days. The average ICO distributes 61% of generated tokens to the public. Therefore, founders on average retain 39% of tokens. The bonus fluctuates between zero and 1000%, and is 25% on average. A bonus of 25% implies that when you buy one token and you fulfil specific criteria, you receive 1.25 tokens instead. Note that we always capture the highest possible bonus during the main sale.

[12] Plotting the residuals of the regressions from our main specification, we find no deviation from the assumption of normal distributed standard errors except for heteroskedasticity. Therefore, we estimate heteroskedasticity-consitent standard errors. Moreover, using log-transormed *raised mUSD* does not significantly change the results of our investigations. Regression results are available upon request.

[13] The EOS ICO, for example, collected more than US$4 billion, however, over several sale events from June 2017 until June 2018.

TABLE 4

REGRESSION OF *RAISED MUSD* ON QUALITY SIGNALS

	Model 1: All observations			Model 2: Subsample of ICO projects running a Twitter account before ICO		
	(1)	(2)	(3)	(4)	(5)	(6)
raised mUSD	Coefficient	Beta	*t*-statistic	Coefficient	Beta	*t*-statistic
Human capital						
team size	0.029	0.008	0.182	0.042	0.012	0.235
share university degree	1.025	0.013	0.441	1.080	0.013	0.348
number advisors	–0.073	–0.012	–0.325	–0.129	–0.022	–0.515
Self-efficacy						
duration	–0.134***	–0.165***	–4.557	–0.122***	–0.146***	–3.706
distributed percent	–7.770*	–0.085*	–1.696	–10.725*	–0.103*	–1.683
bonus	–2.843**	–0.081**	–2.252	–3.148*	–0.082*	–1.870
Ambiguity reduction						
Risks	–1.359	–0.027	–0.698	–2.072	–0.038	–0.793
disclaimer	2.329	0.052	1.223	3.310	0.068	1.385
Media presence						
social count	2.099***	0.232***	4.671	2.396***	0.176***	3.659
Twitter activity				0.017*	0.080*	1.916
Additional controls						
token price	–0.001	–0.016	–0.962	–0.001	–0.010	–0.432
pre-sale	–2.938*	–0.067*	–1.648	–4.367*	–0.090*	–1.713
goal mUSD	0.164***	0.306***	2.779	0.196***	0.343***	2.651
Constant	5.938		0.552	20.802*		1.949
Observations	664			521		
R-squared	0.314			0.340		
Month-year FE	YES			YES		
Industry FE	YES			YES		
Token form FE	YES			YES		
Country FE	YES			YES		

This table presents results from ordinary least squares linear regressions (using robust standard errors) with the absolute funding amount (*raised mUSD*) as the dependent variable. Variables are as defined in Table 1. We use fixed effects for time (month-year), industry, token form (utility token, security token or currency token), and the ICO project's country of origin. *T*-statistics in parentheses: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

As can be inferred from Panel D, only 22% of ICO white papers present potential risk factors, while about 34% provide a legal disclaimer.

Panel E provides information about the level of media presence of ICO projects before the token sale. Projects run three social media channels on average. However, while the maximum of *social count* is eight, more than 25% of the projects in our sample use no social media channel at all. The mean of *Twitter activity* is 64.30, implying that the average ICO Twitter account posts about 64 tweets in the 60 days pre ICO. However, the median of the variable is only 29, showing that the mean is driven by a few projects that write many tweets (up to 1,087) pre ICO.

Controls (Panel F) show that the token price is US$15.66 on average, while the median price of one token is US$0.30. As many projects state the token price in Bitcoin or Ethereum, the corresponding US dollar price is subject to significant

TABLE 5

USING SELECTION ON OBSERVABLES TO ASSESS BIAS FROM UNOBSERVABLES

Explanatory variable of interest	Full model	δ	Beta range
duration	Controls + Month-Year FE + Industry FE + Token Form FE + Country FE	2.260	[–0.100, –0.122]
distributed percent	Controls + Month-Year FE + Industry FE + Token Form FE + Country FE	2.562	[–8.759, –10.720]
bonus	Controls + Month-Year FE + Industry FE + Token Form FE + Country FE	14.110	[–3.177, –3.148]
social count	Controls + Month-Year FE + Industry FE + Token Form FE + Country FE	4.374	[2.329, 2.396]
Twitter activity	Controls + Month-Year FE + Industry FE + Token Form FE + Country FE	2.786	[0.013, 0.017]

This table presents the results of Oster's (2019) test for unobservable selection and coefficient stability. δ is the degree of selection on unobservable variables relative to observed variables that would be necessary to explain away the results given the full model specifications. It is calculated as $\frac{\beta_{full}}{\beta_{restricted}-\beta_{full}} \cdot \frac{R_{full}-R_{restricted}}{R_{max}-R_{full}}$, where β_{full} is the coefficient of our explanatory variable of interest using the full set of controls as presented in column (4) of Table 4, while $\beta_{restricted}$ is the coefficient of our explanatory variable of interest from the model using the variable of interest as the explanatory variable only. R_{full} and $R_{restricted}$ are the R-squares of the particular regression models, while R_{max} is the R-square of a hypothetical estimation that includes both observable and unobservable variables. We follow Oster's (2019) recommendation by setting $R_{max}$to 1.3*R_{full}. The beta range is $[\beta^*, \beta_{full}]$, where β^* is the bias-adjusted treatment effect that is calculated as $\beta^* = \beta_{full} - \left(\beta_{restricted} - \beta_{full}\right) * \frac{R_{max}-R_{full}}{R_{full}-R_{restricted}}$.

fluctuations. For instance, the minimum Bitcoin price in our sample period was US $572, while the maximum price was US$19,479. More than 50% of the projects offer a pre-sale before the main sale event. The mean of *goal mUSD* is more than US$29 million, while the median is US$15.01 million.

Table 2 presents the correlation matrix of our variables. Our main variable of interest and proxy for ICO success (*raised mUSD*) is positively correlated to *team size* and the number of advisors, indicating a positive relationship between ICO success and human capital. However, there is no correlation between *raised mUSD* and the share of team members holding a university degree. Moreover, *raised mUSD* is statistically significantly related to all three proxies for entrepreneurs' self-efficacy (*duration*, *distributed percent*, *bonus*). As higher values of those variables indicate a lower self-efficacy, negative signs of the correlations indicate a positive relationship between entrepreneurs' self-efficacy and ICO success. There seems to be no linear relationship between our proxies for ambiguity reduction, namely *disclaimer* and *risks*, and ICO success. However, the level of (social) media presence (*social count* and *Twitter activity*) is positively related to ICO success. Overall, the correlations suggest that human capital, entrepreneurs' self-efficacy, and media presence are effective signals within the ICO context.

Apart from linear relationships between explanatory variables and ICO success, there are also relationships between several of our explanatory variables. In particular, *pre-sale* and *social count* are statistically significantly related to most of our other explanatory variables. To assess potential collinearity issues in our main regression models, we calculate the variance inflation factors (VIF) for all our model specifications. We find a maximum VIF of 1.61 indicating no severe collinearity issues in our regressions.

RESULTS AND DISCUSSION

Mean Differences Tests

The correlation matrix presented above provides a first glimpse on potential relationships between our explanatory variables and ICO success. To obtain further insights into the relationship between quality signals and ICO success, we apply a mean difference test. Therefore, we perform a median split according to *raised mUSD* and then compare the means of our explanatory variables for the resulting sub-samples. Table 3 presents the results.

Regarding human capital, we find a significant difference between the below median group of *raised mUSD* and the above median group of *raised mUSD* for two out of three variables. While the average team size of projects in the below median group is 3.72, the average of team size of projects in the above median group is nearly twice as high at 6.30. The number of advisors is even more than twice as high for projects in the above median group (2.80) compared to projects in the below median group (1.24). The number of people involved in a project positively relates to ICO success, while the education of the team members does not. Overall, evidence from the mean difference tests suggest that human capital is an effective signal for venture quality.

In line with the correlation results, the mean difference tests for our proxies for entrepreneurs' self-efficacy are statistically significant. All three tests indicate that a higher self-efficacy leads to a higher ICO funding amount. The mean difference is most striking for ICO duration. While ICOs in the below mean group on average show a duration of more than 41 days, ICOs in the above median group only show an average of about 26 days.

Again, we find no evidence of a relationship between our proxies for ambiguity reduction and *raised mUSD*. Hence, investors seem not to perceive the existence of a legal disclaimer or a passage about potential risk factors as a signal for project quality.

For the proxy variables for the level of media presence, on the other hand, we find statistically significant mean differences. On average, projects in the above median group use 1.94 more social media channels than projects in the below median group. Moreover, project initiators in the above median group write on average 28.87 more Twitter messages in the 60 days before the token sale event than the project initiators in the below median group. Note that we lose observations for ICOs that had no Twitter account before the token sale event. In sum, results indicate that media presence effectively affects funding success. Lastly, tests for our controls show no significant mean differences.

Multiple Regression Results

In this section, we analyze the explanatory factors of ICO success within a linear regression framework. Results are presented in Table 4.

The dependent variable of our analysis is *raised mUSD*. The explanatory variables comprise proxies for human capital, entrepreneurs' self-efficacy, ambiguity reduction, and level of media presence as well as further control variables. Table 4 includes two different regression models. The first model includes all observations with data points for *raised mUSD* and for our variables obtained from the projects' white papers but excludes the variable *Twitter activity*. The second regression model includes *Twitter activity* and, therefore, we lose observations for ICOs that had no Twitter account before the token sale event. In both regressions, we use four types of fixed effects. First, we use fixed effects for time (month-year) as market cycles exist in the ICO market (Masiak *et al.*, 2019). In addition, we use fixed effects for industry[14] and token form (utility token, security token, or currency token) and the ICO project's country of origin. Moreover, we use robust (heteroskedasticity-consistent) standard errors for both estimations.

There are 664 observations in our first estimation. We are able to explain 31.4% of the variation of *raised mUSD*. Column (1) shows regression coefficients of our first model. With regard to human capital, the significant correlations between *raised mUSD* and *team size* and *number advisors*, respectively, vanish when we control for other factors that are related to *raised mUSD*. Hence, there is no

[14] Following the project descriptions in the projects' white papers, we identified the following industries: data service, exchange, financial services, gambling, gaming, healthcare, investment vehicle, marketing, marketplace, media, real estate, security, social network, software, and other.

significant linear relationship between *raised mUSD* and any of our three proxy variables for human capital in our multiple regressions. Therefore, we reject our Hypothesis 1, that human capital positively affects ICO funding success. Our results suggest that human capital is no significant signal for project quality from an ICO investor's point of view. In this regard, ICOs seem to differ from conventional crowdfunding investment (Ahlers *et al*., 2015; Barbi and Mattioli, 2019; Piva and Rossi-Lamastra, 2018). We argue that human capital plays a less important role from an ICO investor's perspective as ICO projects on average are much larger than conventional crowdfunding campaigns (see above). Consequently, stronger inter-personal ties between backers and investors than in ICO campaigns characterize conventional crowdfunding campaigns.

The coefficients for *duration*, *distributed percent*, and *bonus* confirm our results from the correlation analysis (see Table 2) and the median split (see Table 3). The coefficients are statistically significant and each shows a negative sign. For every day less that an ICO last, it collects US$134,000 more. This finding is in line with the literature showing that IPOs with a shorter duration are perceived as less risky (Brooks *et al*., 2009). Moreover, for one percentage point of tokens less distributed to the public (and thus one percentage point of tokens more reserved by the ICO founders), an ICO collects US$78,000 more. We argue that a low share of tokens distributed to the public indeed signals entrepreneurs' confidence in the value of their project, lowers the level of uncertainty and, following the entrepreneurial ownership retention hypothesis (Leland and Pyle, 1977), is positively related to project value and ICO success. This is in line with the literature which finds that ownership retention is positively related to firm value after an IPO (Downes and Heinkel, 1982). Lastly, for a one-percentage-point lower bonus, an ICO collects US$28,000 more. This conforms to the literature stating that customers may perceive high discounts as a signal for insufficient project quality (Gwinner *et al*., 1998). Overall, evidence supports our Hypothesis 2. Entrepreneurs' self-efficacy is an important signal for project quality from an ICO investor's point of view.

With regard to the ambiguity reduction, we detect no significant relationship between used proxies and *raised mUSD*. Coefficients for both, *risks* and *disclaimer*, do not significantly differentiate from zero. This, again, is in line with our prior results (see Tables 2 and 3) and the literature on crowdfunding (Ahlers *et al*., 2015). Thus, evidently, ICO investors do not care about the declaration of potential risks or legal information about the investment. In conclusion, we argue that, contrary to Hypothesis 3, ambiguity reduction is not a signal of quality for ICO investors.

With regard to media presence, however, evidence supports our hypothesis H4. We find that media presence is an important factor of ICO success. For each social media platform a project uses, it is able to collect US$2.10 million more. Results are in line with our prior investigations (see Tables 2 and 3). Moreover, investigations on conventional crowdfunding find similar relationships (Barbi and Mattioli, 2019; Lukkarinen *et al*., 2016). To achieve deeper insights into the role of social media, we include the Twitter activity of the projects in our second regression model.

Controls reveal that the *token price* is not related to the amount of US dollars raised. As the token price is arbitrarily divisible, this result is not a surprise. Projects with a pre-sale collect about US$3 million less on average. A possible interpretation for this finding is that those projects attract institutional investors during the pre-sale who then do not invest during the main sale event. The literature on conventional crowdfunding, however, finds a positive relationship between the availability of a pre-sale and funding success (Barbi and Mattioli, 2019; Lukkarinen *et al.*, 2016). We argue that ICOs differ from conventional crowdfunding in this regard as the pre-sale at conventional crowdfunding is often exclusively directed towards institutional investors. The involvement of institutional investors may convey credibility in the crowdfunding project (Lukkarinen *et al.*, 2016). In ICOs, however, the pre-sale is open to the public as well. Consequently, the ICO pre-sale is a substitute for the actual main sale, possibly reducing the funding amount in the ICO main sale. Lastly, projects with a higher goal or cap attract more funds. For a one-dollar higher goal, an ICO project is able to collect an additional 16.4 cents. However, this result has to be interpreted with caution because of the fact that projects often state no real goal but only specify a soft cap or hard cap.

As mentioned before, we deploy a second regression model to investigate the role of the ICO projects' Twitter activity. Results can be obtained from columns (4) to (6) of Table 4. We only include ICOs in our estimation that had a Twitter account before the token sale event. Consequently, the number of observations drops to 521. However, the R-squared increases to 34%. Moreover, the constant increases significantly and is now statistically significant at the 10% level. By implication, this increase means that this sub-sample contains ICOs that are more successful. This is not surprising as the prior regression shows that ICOs that use more social media channels attract more investments.

With regard to Twitter activity, the regression coefficient is positive and statistically significant. For each Twitter message in the 60 days before the ICO, an ICO project is able to collect US$17,000 more. Thus, media presence is an effective signal for entrepreneurs to induce investors to invest in an ICO. This, again, supports our Hypothesis 4.

The other variables do not change notably among the two regression models, thus indicating the high robustness of our results.

Overall, entrepreneurs' self-efficacy and level of media presence constitute effective signals from the viewpoint of (potential) ICO investors. Evidence suggests, however, that human capital and ambiguity reduction are less important for investors.

Assessing the Potential Bias from Unobservable Omitted Variables

Our main regressions are able to explain up to 34% of the variation of *raised mUSD*. Therefore, like many other empirical studies, a large part of the variation of our dependent variable remains unexplained, possibly resulting in an omitted variable bias. While we are not able to fully rule out the existence of this bias, we can assess the importance of selection of unobservable variables. Following Oster's (2019) method, we calculate δ for each of our proxies for entrepreneurs' self-efficacy and level of media presence. δ specifies how large the share of variation of *raised mUSD* that unobservable variables are able to explain relative to the share of variation explained by the control variables included in our regression model needs to be, to diminish the estimated effect of our explanatory variables of interest on ICO success. Therefore, we calculate

$$\delta = \frac{\beta_{full}}{\beta_{restricted} - \beta_{full}} \cdot \frac{R_{full} - R_{restricted}}{R_{max} - R_{full}}, \tag{1}$$

where β_{full} is the coefficient of our explanatory variable of interest using the full set of controls from our regression model in the previous section, while $\beta_{restricted}$ is the coefficient of our explanatory variable of interest from the model using the explanatory variable of interest only. R_{full} and $R_{restricted}$ are the R-squareds of the particular regression model, while R_{max} is the R-squared of a hypothetical estimation that includes both observable and unobservable variables. We follow Oster's (2019) recommendation by setting $R_{max}$to 1.3 * R_{full}. Table 5 presents the results.

Results imply that the explanatory power of a potential omitted variable has to be 2.3 (*duration*) to 14.1 (*bonus*) times higher than the actual explanatory power of our full regression model to eliminate the effect of our explanatory variable of interest. Oster (2019) suggests that a δ of more than one is an indication that there is no significant omitted variable bias in the given regression model. Therefore, we argue that omitted variables are not a serious issue in our investigation. Moreover, the beta range in Table 5 provides a range for the coefficients of our explanatory variables of interest when adjusting our estimations for a potential unobservable omitted variable effect. As none of the beta ranges enclose zero, results suggest that estimated coefficients are still different from zero.

LIMITATIONS

Although our empirical results are based on a comprehensive database of mainly manually collected information and seem to be robust to omitted variable bias as suggested by the findings of the Oster (2019) test, our study may suffer from some limitations and remaining questions, respectively.

First, the principles of ICOs, and thus the anonymity of ICO investors, prevent us from gaining deeper insights into individuals investing in ICO projects. Therefore, we are not able to analyze investor characteristics, such as demographic factors or professional expertise, and their impact on investment behaviour. Moreover, we are unable to identify investors' underlying motives with certainty. While we assume that investors are motivated by monetary rewards in the first place, non-monetary rewards, such as access to future products and services as granted by utility tokens, might be more important for some investors. We try to take this into account by including fixed effects for the type of issued tokens in our main specifications.

Second, many of our variables only serve as proxies for broader concepts, for example, we measure human capital signals by the size of the project team and the share of team members that holds a university degree. Due to the limited information provided by ICO initiators, however, we also assume that potential investors do not have more relevant information. Therefore, our used proxies might be a close approximation of the respective quality signals. Moreover, our proxies are used in other relevant studies (e.g., Ahlers *et al.*, 2015).

Third, our data might be subject to selection bias. Since we derive our initial ICO sample from online ICO information platforms, our statistical population is restricted to ICOs that are included on those platforms. We try to minimize the potential selection bias by incorporating data on ICOs from seven different ICO information platforms. Nevertheless, some ICOs might take place without being represented on any of those information platforms.

Fourth, it seems promising to obtain an in-depth understanding of signalling in ICOs by investigating various ICO subgroups. The effects we find in our major specifications might differ for different ICOs' countries of origin, token form, or company age. Unfortunately, our final sample consists of only 662 ICOs and because we include 14 explanatory variables as well as fixed effects for month-year, industry, token form, and country, our sample is too restricted to perform further subgroup analyses.

Fifth, as presented in the previous chapter, results from the test proposed by Oster (2019) reveal that it is very unlikely that our regression models suffer from a omitted variables bias. However, we cannot rule out that other ICO characteristics, which we do not consider or are unobservable, might be effective signals in the ICO context.

CONCLUSION

This paper investigates which project signals provided by ICO initiators encourage investors to invest financial resources in an ICO context. Using data directly obtained from ICO white papers that are timestamped and therefore guaranteed to have been released before the ICO event, we highlight the importance of media presence and entrepreneurs' self-efficacy for ICO success. However, surprisingly, human capital as well as factors that reduce ambiguity (providing a disclaimer and information on potential risks) do not seem to determine ICO success. Thus, familiarity with an ICO project among potential investors and entrepreneurs' self-efficacy are particular drivers of funding success in the ICO context.

The implications of our main findings are manifold. For entrepreneurs who attempt to conduct an ICO, our findings can provide guidance. For example, it seems that engaging actively in social media activities before a token sale achieves positive results. Moreover, a short ICO duration, high share of tokens retained by the ICO initiator, as well as a low bonus provided to investors are effective signals that can increase funding success.

Furthermore, with respect to policy implications, our findings emphasize investors' differentiated assessment of potential investment opportunities in the ICO context. However, we highlight investors' indifference regarding the provision of legal disclaimers and potential risk factors. Against a background of a high number of scams in the ICO market, it is necessary to sensitize potential investors to underlying risks.

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APPENDIX A DESCRIPTIONS OF VARIABLES

Table A1 contains descriptions and construction details of all variables used in this paper.

TABLE A1

DESCRIPTIONS OF VARIABLES

	Variable	Unit	Explanation
ICO success	*raised mUSD*	US$	Amount raised by the project during the ICO main sale period in millions of US dollars.
Human capital	*team size*	#	Number of members in the project team.
	share university degree	%	Share of the team members who hold a university degree.
	number advisors	#	Number of advisors of the ICO project.
Entrepreneurs' self-efficacy	*duration*	Days	Duration of the ICO main sale in days.
	distributed percent	%	Share of tokens distributed to the public during the ICO main sale period.
	bonus	%	Maximum bonus granted to investors during the ICO main sale period.
Ambiguity reduction	*risks*	1/0	Dummy variable that equals one if there is a section in the ICO white paper that declares potential risk factors of the ICO (investment), and zero otherwise.
	disclaimer	1/0	Dummy variable that equals one if there is a (legal) disclaimer in the ICO white paper, and zero otherwise.
Media presence	*social count*	#	Number of social media platforms the ICO project uses.
	Twitter activity	#	Number of tweets the ICO project posted in the 60 days before the start of the ICO main sale.
Controls	*token price*	US$	Price of the issued tokens during the ICO main sale period in US dollars.
	pre-sale	1/0	Dummy variable that equals one if there was a pre-sale before the ICO main sale, and zero otherwise.
	goal mUSD	US$	Fundraising goal of the ICO project in US dollars.

APPENDIX B DATA PROCESSING PROCEDURE

We started the empirical analysis by obtaining an initial sample from the ICO information platform icotracker.net. Our investigation covers the period 1 July 2014 to 31 January 2018. Based on this initial list of ICO projects, we searched the remaining considered ICO information platforms, namely smithandcrown.com, icodata.io, icobazaar.com, tokendata.io, icobench.com, and icodrops.com, for further ICO projects and added them to our initial sample. This process—after manually removing duplicates and ICO pre-sales—resulted in a sample of 1,679 ICO projects. For these ICO projects, we obtained data on raised funds as well as data on ICO projects' country of origin from all aforementioned ICO information platforms. Since not all ICO information platforms provide data for every project in our sample and, in addition, the data points partially overlap, we decided to prioritize the platforms according to their data coverage. Thus, we derived data from the platforms in the following order: icodata.io, tokendata.io, icobench.com, smithandcrown.com, icodrops.com, icotracker.net, and icobazaar.com. Here, the first platform covers 621 ICOs whereas the last platform provide data on 122 ICOs. Deriving data from seven different ICO information platforms enabled us to retrieve as many ICOs as possible and thus reduce a potential selection bias. As we are interested in the ICOs' funding success, we removed all observations without any information on raised funds. Overall, this procedure resulted in a sample of 1,057 ICO projects.

Based on this sample, we searched for ICO white papers on the ICO projects' websites. If a project's website was not available or did not provide a white paper (or only a white paper that dated from after the ICO period), we searched all aforementioned ICO information platforms for these white papers. Overall, we obtained white papers for 863 ICO projects. We used these white papers to manually derive all of our explanatory variables, except for the variables on media presence. Two independent coders reviewed all white papers and a common consensus was reached in case of differences between the two coders.

Lastly, we investigated the presence of each ICO project on eight different social media platforms, namely Twitter, Facebook, Bitcointalk, Github, Reddit, Telegram, Medium, and Slack. Here, for each social media platform, we used a dummy variable equals to one if an ICO project was represented on the respective platform, and zero otherwise. Additionally, we investigated ICOs' Twitter accounts more deeply to assess their social media activity. In particular, we web

TABLE B1

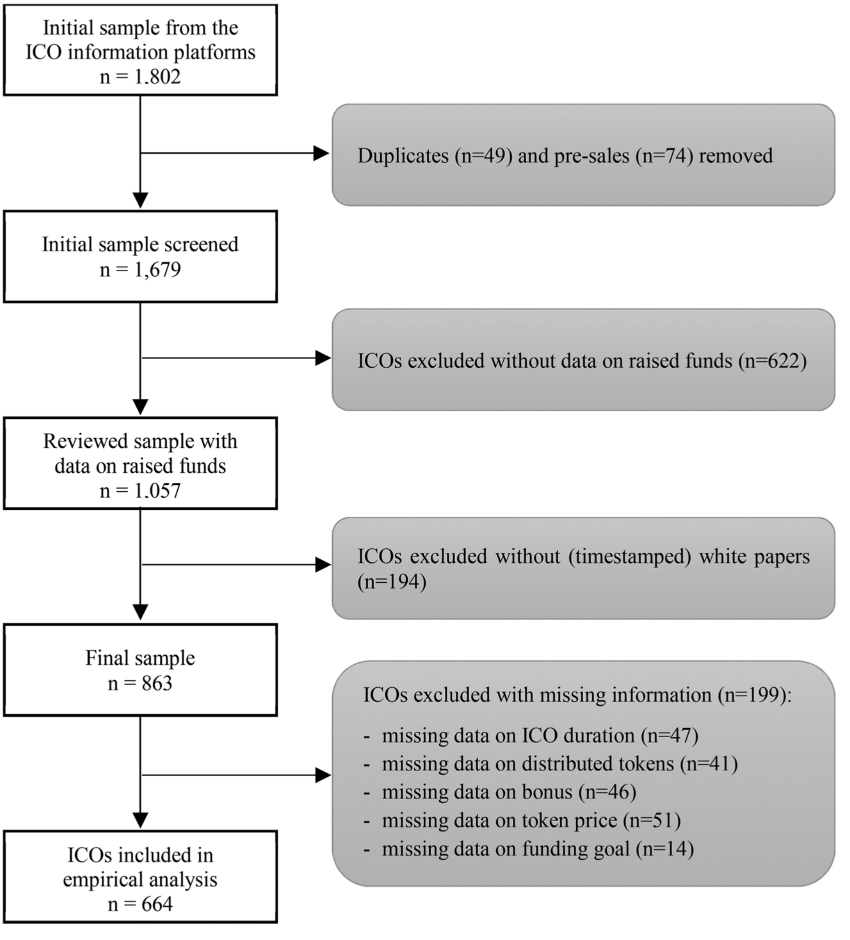
OVERVIEW OF DATA SOURCES

Source	Derived variables
ICO information platforms, i.e., icodata.io, tokendata.io, icobench.com, smithandcrown.com, icodrops.com, icotracker.net, icobazaar.com	*raised mUSD* Also: information on ICO projects' country of origin
White papers	*team size, share university degree, number advisors, duration, distributed percent, bonus, risks, disclaimer, token price, pre-sale, goal mUSD* Also: information on token form and industry
Social media websites, i.e., Twitter, Facebook, Bitcointalk, Github, Reddit, Telegram, Medium, Slack	*social count*
Twitter	*Twitter activity*

This table shows our sources of data and derived variables from these sources.

FIGURE B1

FLOWCHART



This figure shows the data collection and cleaning process.

scraped the Twitter timelines of each ICO project represented on Twitter using R. Overall, we obtained Twitter data containing the content as well as the metadata on each tweet until January 2018 for 774 ICO projects.

Please see Table B1 for an overview of data sources and the corresponding derived variables and Figure B1 for the data collection and cleaning process flowchart.