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Entrepreneurial Finance and Moral Hazard: Evidence from Token Offerings☆

Paul P. Momtaz

UCLA Anderson School of Management, 110 Westwood Plaza, Suite C.402, CA Los Angeles, 90095, United States of America

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ABSTRACT

This paper provides the first evidence of a *moral hazard in signaling* in an entrepreneurial finance context, by examining token offerings or Initial Coin Offerings (ICOs). Entrepreneurs' ability to signal quality is crucial to succeeding in the competition for growth capital. However, the absence of institutions that verify endogenous signals may induce a moral hazard in signaling. Consistent with this hypothesis, artificial linguistic intelligence indicates that token issuers systematically exaggerate information disclosed in whitepapers. Exaggerating entrepreneurs raise more funds in less time, suggesting that investors do not see through this practice initially. Eventually, the crowd learns about the exaggeration bias through trading with other investors. The resulting investor disappointment causes the cryptocurrency to depreciate and the probability of platform failure to increase.

1. Executive summary

Token offerings or Initial Coin Offerings (ICOs) are smart contracts programmed on distributed ledger technology (DLT), which are designed to raise external finance without the need for an intermediary by issuing tokens or coins that can be publicly traded.[1] The main innovations of token offerings are that they allow entrepreneurs to raise growth capital at close-to-zero transaction costs by cutting out the intermediary, and that they provide entrepreneurs with anytime-exit opportunities through the option to sell their retained tokens on exchange platforms. Token offerings have experienced soaring levels of adoption from ventures since 2017. While 661 ventures conducted token offerings in 2017, more than 4500 ventures sold tokens in 2018.[2] The market is also substantial in terms

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E-mail address: momtaz@ucla.edu.

[1] Most studies use the terms token sales and ICOs interchangeably, although the term ICO is potentially misleading. Most token sales fix the maximum token supply as immutable terms in the underlying smart contract. Hence, there is no initial and then a subsequent coin offering, but just the one. Hence, *token sale* or *token offering* should be preferred over ICO. Furthermore, the distinction between tokens and coins is that coins are created on their own blockchain, whereas tokens are applications built upon existing blockchains (Momtaz, 2019b).

[2] Information available from https://icobench.com/stats. Retrieved on January 15, 2019.

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of the volume raised. The cumulative funding amount already exceeds the entire European venture capital industry, and the largest token offering so far (*EOS*, $4.2b) is comparable in size to the three largest IPOs in the same time period. It also exceeds the cumulative funding amount of all crowdfunding initiatives of the premier platform (*Kickstarter*) since its inception in 2009.[3]

The literature on token offerings is still in its infancy. Initial work examines the determinants of the funding amount (Fisch, 2019), short-run performance of token offerings (Kostovetsky and Benedetti, 2018; Momtaz, 2018) as well as long-run performance (Momtaz, 2020b), token liquidity (Howell et al., 2018), and the role of institutional investors in ICOs (Fisch and Momtaz, 2020), with many more research papers currently in progress. Much of this early work is limited in the sense that it provides descriptive studies but lacks a conceptual framework, with the notable exception of Fisch (2019). Drawing on the crowdfunding literature (Ahlers et al., 2015; Mollick, 2014; Vismara, 2016, 2018), Fisch (2019) suggests using signaling theory to explore how token issuers attract investors.

This paper argues, both theoretically and empirically, that in the context of token offerings, the role of signaling has to be viewed with caution, because the unique institutional framework of token offerings might induce a *moral hazard in signaling*. A moral hazard occurs if one transacting party has an incentive to engage in dubious behavior at the expense of its counterparty (Hurt, 2004). In token offerings, issuers plausibly have an incentive to bias signals of venture quality to their advantage because there currently are neither functioning institutions that verify signals *ex ante* nor are there those that punish signals *ex post* once the bias is detected.[4] If investors are attracted to the ventures with the most positive signals and fail to identify biased ones, then firms which are not sending biased signals may experience a competitive disadvantage. This effectively creates a moral hazard in signaling. Importantly, my reasoning provides an explanation for the vast number of documented 'exit scams'[5] in token offerings (>85%) (Malinova and Park, 2018).

This paper hypothesizes that *manifestations of moral hazard* are tied to the ability of dispersed investors to observe the wisdom of the crowd. Dispersed investors are individually too small to have an incentive to reduce informational asymmetries on their own in order to be able to verify whether a signal is truthful or not (Becht et al., 2003). This creates an environment in which biased signals may go undetected, rendering it profitable for ventures to send biased signals. In this paper, this is referred to as the *asymmetric information hypothesis*. The situation plausibly changes when the token is listed on an exchange platform. Supply and demand dynamics form an equilibrium token price; a fair valuation of the venture, reflecting all available information from all dispersed investors. It can be argued that the equilibrium price of listed tokens reflects the wisdom of the crowd, which is transparent and readily observable for all dispersed investors. With this information, dispersed investors are able to adjust their venture valuation. Biased signals backfire on the venture because investors will sell these tokens, which creates downward price pressure. In fact, the negative momentum may even hasten platform failure if network effects fail to appear because of potential investor deterrence. In this paper, this is referred to as the *crowd-learning hypothesis*. In summary, the theory outlined predicts that under the asymmetric information hypothesis, biased signals are profitable until trading begins (faster time to market and higher funding amount), whereas under the crowd-learning hypothesis, biased signals backfire as soon as trading begins (lower returns and more likely venture failure).

The empirical results confirm the existence of a systematic moral hazard in signaling. Using artificial linguistic intelligence on an international sample of 495 token offerings, it was found that token issuers systematically exaggerate information disclosed in whitepapers. The consequences of manifestations of the moral hazard occurring in signaling in the form of an *informational exaggeration bias*, are consistent with the theoretical predictions. As long as tokens are not traded, ventures sending biased signals perform better, in that they raise significantly more funds in significantly less time. However, in line with the 'wisdom of the crowd' notion of publicly traded token prices, biased signals backfire once trading begins. Biased signals are associated with significantly lower initial returns. Interestingly, they are also characterized by a higher initial price volatility that gradually decreases, which reflects investor learning about the true venture quality. Eventually, ventures with biased signals are more likely to fail. Overall, the findings collectively lend support to both the asymmetric information hypothesis and the crowd-learning hypothesis, as well as highlighting the role token trading plays as a corrective for the moral hazard in signaling; created by the absence of institutions in the infant market for token offerings.

The study contributes to the literature on entrepreneurial finance in several ways. It extends Fisch's (2019) seminal work on the determinants of the funding amount in token offerings to other relevant market characteristics such as the time to market, returns, and long-term platform success. It also contributes to theory by offering a critical perspective on the role of signaling in entrepreneurial finance. Importantly, this study provides an explanation for the large amount of documented 'exit scams' in token offerings (Kean, 2018; Shifflett and Jones, 2018). Absent functioning institutions that create trust (Rhue, 2018), a moral hazard in signaling might occur. This has important implications for practitioners such as investors and policy-makers. In the enduring absence of institutions that ex ante verify signals or ex post punish biased signals, token offerings might turn into a 'market for lemons' (Akerlof, 1978; Chod and Lyandres, 2018).

2. Introduction

New ventures require financial resources to grow (Gompers and Lerner, 2004), and the competition for growth capital is fierce

[3] References for these three comparisons are Howell et al. (2018), Fisch (2019), Adhami et al. (2018), and Momtaz, 2019b.

[4] It is helpful to recall that signaling theory was developed in a context with functioning institutions (labor market: laws, workers unions, employers associations, informed market participants, etc.) (Spence, 1973). Similar institutions do not yet exist for token offerings (Zetzsche et al., 2018).

[5] So-called *exit scams* refer to fraud schemes in which start-ups exert or pretend to exert effort to build a successful platform only until some point after a successful fundraising campaign, and then abandon the start-up with the raised funds for private benefit.

(Chemmanur and Fulghieri, 2013; Denis, 2004). Nevertheless, a number of different funding sources and mechanisms that are tailored to the specific needs of entrepreneurs exists, such as Initial Public Offerings (e.g., Ritter and Welch, 2002), venture capital (e.g., Gompers and Lerner, 2004; Busenitz et al., 2005), crowdfunding (e.g., Mollick, 2014; Ahlers et al., 2015), business angels (e.g., Elitzur and Gavious, 2003), and now token offerings. Token offerings or Initial Coin Offerings (ICOs) are a recent phenomenon but the market is soaring (Adhami et al., 2018; Amsden and Schweizer, 2018; Momtaz, 2018, 2020b), even though it is plagued with a vast amount of scams (Kean, 2018; Shifflett and Jones, 2018). A limitation of the early literature on token offerings is its lack of conceptualization of token offering dynamics. In a seminal study, Fisch (2019) applies signaling theory to examine the dynamics of the funding amount in token offerings.

This paper takes a critical perspective on the role of signals in token offerings. At the core of the argument is the observation that, unlike other contexts in which signaling theory has been successfully applied such as crowdfunding (Ahlers et al., 2015; Vismara, 2016, 2018),[6] the market for token offerings lacks an institutional framework that would guarantee the efficiency of signals. Because signals are neither verified *ex ante* nor punished *ex post*, a *moral hazard in signaling* might occur if investors fail to reliably detect biased signals (Leland and Pyle, 1977). Therefore, this study seeks to address the research question: How does a potential moral hazard in signaling shape various economic outcomes in the market for token offerings?

This study makes several novel contributions to the literature on signaling in entrepreneurial finance and on the emerging literature on token offerings in general. First, the conjecture that manifestations of moral hazard in signaling become evident only after tokens are traded may help explain the aggregate ICO market pattern that the number and the volume of ICOs is decreasing since Q2/2018 when large investor disappointment about exaggerated signals became public (e.g., Shifflett and Jones, 2018). Second, my study extends Fisch' s (2019) signaling-related evidence by looking at additional outcome variables such as time-to-funding, funding technique, token price volatility, initial returns, delistings, and venture failure. Finding that exaggerated signals can have diametrically opposed effects on the various outcome variables, as I hypothesize, may highlight the importance of considering a comprehensive set of dependent variables. Third, a key novelty for research in entrepreneurial finance is that (changes in) the firm value of start-ups become readily observable at daily frequency when the token is listed shortly after the ICO. Firm values in the context of other start-up financing mechanisms such as VC become available often only years after the initial funding round when the start-up is acquired or goes public. Hence, exploiting daily token prices helps opening up the black box of how ventures evolve between the initial funding round and when the start-up is already an established player in the industry. Fourth, while moral hazard is a long-standing concept in entrepreneurial finance, the use of a machine-learning algorithm from the computational linguistics literature to quantify informational exaggeration in ICO whitepapers as a manifestation of moral hazard in signaling and relating that measure to economic outcomes is a key novelty of my study.

In what follows next, I provide some theoretical background, develop testable hypotheses, describe data and methodology, present empirical results, and discuss the results, implications for theory and practice, limitations of the study, and potential avenues for future research.

3. Theoretical background

This section describes why, in the context of token sales, a *moral hazard in signaling* might occur. The intuition is that with increasingly fierce competition for growth capital and absent institutions verifying signals and punishing biased ones, ventures that report truthfully might have a competitive disadvantage over those sending biased signals. This section establishes the sources of asymmetric information and the limitations to signaling, which collectively lead to the occurrence of moral hazard. It then concludes by hypothesizing that (i) manifestations of moral hazard are profitable for token issuers as long as dispersed investors are unable to aggregate the wisdom of the crowd; whereas (ii) manifestations of moral hazard backfire as soon as the wisdom of the crowd becomes readily observable through supply-and-demand dynamics on token exchange platforms.

3.1. Asymmetric information in the context of token sales

Asymmetric information is a pervasive problem in financial markets (Jensen and Meckling, 1976); buyers of financial claims lack the information to gauge the true quality of the contract. This results in equilibrium pricing of the financial claims based on the population average instead of a more discriminatory pricing mechanism based on the underlying contract value. Consequently, high-quality contracts would sell at a discount, deterring them from entering the market entirely, which may create a market for lemons (Akerlof, 1978).

Asymmetric information is a key challenge in the context of token sales (Fisch, 2019; Momtaz, 2020a) and the potential for becoming a market for lemons has been made explicit in the model of Chod and Lyandres (2018). Initial evidence about how pronounced the asymmetric information problem is in ICOs comes from Colombo et al. (2020) who show that ICO investors are willing to pay a significant premium on tokens sold by *attractive CEOs*, possibly because of stereotype-based biases. There are at least four distinct origins of informational asymmetries in the context of token sales. First, token sellers are predominantly ventures at a very early stage (Fisch, 2019). Often, these ventures, as well as the entrepreneurs behind them, have neither a proven track record nor a developed product (Howell et al., 2018). Rather, most of them (69%; Momtaz et al., 2019) sell so-called *utility tokens*, which are similar to

[6] Note that the extent of disintermediation in token offerings exceeds even that of crowdfunding. Crowdfunding platforms such as *Kickstarter* at least verify the finance-seeking entity's identity, whereas no institution verifies the basic credentials in token offerings.

vouchers providing the tokenholders with the right to redeem the token for the firm's product or service once it has been developed at an undefined point of time in the future (Momtaz, 2019b). Hence, there is considerable uncertainty about the underlying quality of the entrepreneurial team and the venture idea itself. Furthermore, there is general market uncertainty about the future prospects of DLT (Fisch, 2019; Natarajan et al., 2017).

Second, token sellers are almost exclusively DLT-based ventures (Fisch, 2019). Hence, investors are required to have some technological expertise. Specifically, technological expertise is required, *inter alia*, to open a wallet and partake in a token sale, and to understand the underlying business model, the marketed technological innovation, and the long-term prospects of the venture (Cohney et al., 2018). Yet, due in some part to the infant nature of the DLT- and token-based economy, there are considerable barriers to obtaining technical knowledge. For example, there does not yet exist a terminological standard for key terms such as tokens and coins.[7] The lack of standardization makes it more difficult to obtain technical knowledge, fostering informational asymmetries in token sales.

Third, the absence of private and public institutions promotes informational asymmetries. The ruling paradigm of DLT is to enable parties to transact without intermediaries (Nakamoto, 2008). Yet, intermediaries may have an incentive and the ability to generate information, as seen in the IPO market, which could eliminate informational asymmetries (Benveniste and Spindt, 1989). Furthermore, institutional investors may have both an incentive and the resources to monitor and produce information (Tirole, 2001). However, institutional investors are only gradually entering the market for token sales (Howell et al., 2018; Momtaz, 2019b). As per public institutions, they are largely nonexistent (Zetzsche et al., 2018). First, there are no disclosure requirements pertaining to token sales. Plus, given the infant nature of the market, there are no consistent behavioral norms about the informational content required by investors and hence disclosed by token sellers (Blaseg, 2018). Therefore, token sales are characterized by small amounts of disclosed information (Kaal and Dell'Erba, 2017; Kastelein, 2017; Zetzsche et al., 2018). Even if information is voluntarily disclosed, initial evidence suggests that investors do not trust this information (Blaseg, 2018). On a more fundamental note, it is still unclear to what extent regulatory institutions might be effective at all, given that no national enforcer has the resources or the jurisdiction to prosecute globally distributed blockchain-based platforms.

Fourth, DLT was born out of a preference for anonymity. This feature of DLT-based token sales exemplifies the inherent dilemma: Many market participants (i.e., token sellers, investors, future customers, etc.) require anonymity to partake in transactions, which conflicts with the elimination of informational asymmetries to streamline the functioning of the market for token sales.

3.2. *Disintermediation through smart contracts exacerbates informational asymmetries*

It is instructive to make explicit how disintermediation through smart contracts exacerbates informational asymmetries in token offerings. Smart contracts are automated protocols that define all important transaction parameters (Yermack, 2017). For example, a generic token offering is based on a smart contract, which establishes that an investor wiring amount x to the token issuer receives y tokens (where x/y is the exchange rate) up to a maximum token amount Y that can be issued under the smart contract. It is also important to note that Y is fixed *ex ante* in immutable terms on the blockchain; hence, token issuers cannot subsequently increase the token supply (Iansiti and Lakhani, 2017). It is, for instance, not possible to issue Y tokens at time t and then increase the token supply to $Y + \epsilon$ at time $t + 1$. Hence, the term "initial" in "Initial Coin Offering" is misleading, as there cannot be a "seasoned coin offering" (as an analogue to IPOs and SEOs). This implies that token issuers can tap the finance market only once, which increases the pressure on the venture to raise enough funding to be able to realize the project. It also implies that token issuers have fewer incentives to satisfy investors compared with crowdfunding or IPO firms who may approach their investor base again for additional capital (Benveniste and Spindt, 1989).

In the absence of intermediaries, the increased pressure to raise enough funding and the decreased incentivization to fully satisfy the investor base resulting from the fixed maximum token supply may further exacerbate informational asymmetries. In intermediated transactions, the intermediaries match firms with investors as a business model; hence, these intermediaries have a strong incentive to please investors so as to keep them accessible in future transactions (Ljungqvist, 2007). In game-theoretical terminology, intermediaries play "sequential games", which contrasts with the "one-shot games" played by token issuers (Fudenberg and Tirole, 1991). Therefore, disintermediation in token offerings plausibly creates incentives for token issuers to cultivate informational asymmetries to be exploited to their own advantage (Tirole, 2010). Overall, this reasoning implies that the extent of asymmetric information is more pronounced in token offerings than in intermediated forms of financing.[8]

3.3. *Limitations to signaling and the occurrence of moral hazard*

Signaling theory analyzes how high-quality firms can communicate their type to distinguish themselves from low-quality firms, creating a separating equilibrium (Spence, 1973). This has been applied to several fields in entrepreneurial finance including venture capital (Busenitz et al., 2005), crowdfunding (Ahlers et al., 2015; Anglin et al., 2018; Vismara, 2016), and token sales (Fisch, 2019).

Signaling theory was developed in the context of labor markets in which job applicants want to signal their type to a potential employer (Spence, 1973). This context is characterized by highly sophisticated institutions (e.g., labor laws, worker union, employers'

[7] That is, the precise technical distinction between coins and tokens is that coins are based on their own blockchain, whereas tokens are applications built on an existing blockchain. Yet, most commentators use these terms synonymously.

[8] A comparison between token offerings and other forms of entrepreneurial financing is beyond the scope of this study, but provides a promising avenue for further research.

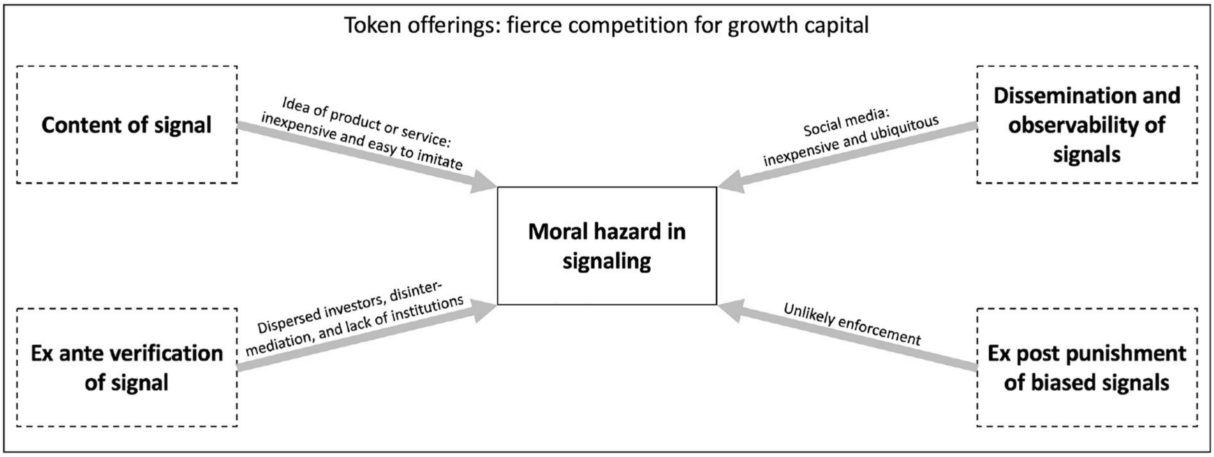

Fig. 1. Limitations to signaling lead to occurrence of moral hazard.

association, etc.) and a receiver of a signal, i.e. the potential employer, that is oftentimes very informed and possesses skills and resources to discriminate between signals (e.g., HR departments). Such a setting might be given in some markets of entrepreneurial finance where there are investor protection laws and sophisticated investors such as venture capital. Then, according to theory, signaling by fundraising firms is an effective means of attracting investors if (i) the signal is observable and (ii) it is costly to imitate (Connelly et al., 2011). However, the ICO market largely lacks informed investors and important institutional features. This might render signaling inefficient. Indeed, initial empirical evidence supports the view that signaling may not work efficiently in token offerings as they document inconclusive results of how, for example, the publication of whitepapers affect the success of token sales (Blaseg, 2018; Fisch, 2019; Howell et al., 2018). In fact, it is argued below that there are at least four practical limitations to signaling, which might foster the occurrence of a moral hazard in signaling, as illustrated in Fig. 1.

The first limitation pertains to the *content of a signal*. Connelly et al. (2011) argue that signals need to be costly or difficult to create and imitate. In the ICO context, the content of signals is not backed by material innovation. Instead, most token issuers only have an idea of a product or service that has yet to be developed (Adhami et al., 2018), which is arguably not costly to imitate. Even more substantial backing (e.g., patents (see Fisch, 2019) does not entail significant effects yet. This may reflect uncertainty about how the market will develop and what will eventually determine the quality of signals. Therefore, at least for the first generation of token offerings, it is inexpensive and relatively easy to create or imitate signals.

A second limitation pertains to the *dissemination and observability of signals*. Another premise of signaling theory is that the signal must be observable (Connelly et al., 2011). In token offerings, signals are disseminated almost exclusively via social media (Blaseg, 2018), creating the ubiquitous observability of signals for all investors, both informed and uninformed. More importantly, signaling via social media is relatively inexpensive. Taken together, the inexpensiveness of creating and disseminating signals minimizes the entry barriers to the ICO market.

Low entry barriers might be a welfare-increasing feature (higher competition) if investors were able to discriminate between high- and low-quality signals. However, there are reasons why the mass of ICO investors lack this ability, and the evidence of so-called exit scams supports this view (Kean, 2018). One reason is that investors in token offerings are dispersed. The presence of many small investors implies that they may lack the skills and resources to verify signals, and they may have problems coordinating the exchange of information among each other (see, for a survey of these corporate governance problems, Becht et al., 2003). Indeed, Boreiko and Vidusso (2018) find that even ICO aggregators such as *ICObench* cannot mitigate this problem. Another reason is that token offerings lack an intermediary. Intermediaries have an incentive to reduce informational asymmetries and to verify the quality of a signal in order to stay on good terms with the investor base for future transactions (Ljungqvist, 2007). Another reason is the lack of functioning institutions (e.g., investor associations, a code of honor, certifying institutions). Taken together, there is a lack of *ex ante verification of signals* that makes it viable to send biased signals.

Low entry barriers and the viability of sending biased signals would not be problematic if it were not be profitable to do so. The only way to achieve this in the given institutional setting would be by *punishing biased signals ex post*. Even the credible threat of *ex post* punishment would suffice as it would deter ventures with biased signals. However, with public institutions not being developed yet (Zetzsche et al., 2018), the enforcement of consequent *ex post* punishment seems unlikely for at least three reasons. First, most token issuers offer utility tokens (Momtaz et al., 2019). Unlike cryptocurrency and security tokens, which are subject to asset and securities laws, respectively, the regulatory framework for utility tokens (if they fail the *Howey test*) is undefined (Howell et al., 2018). Hence, utility token offerings are conducted in a legal grey zone, with the level of investor protection being at a minimum (Kean, 2018). Thus, there is only a limited basis (only broader laws) to pursue legal action after the token offering. Second, tokens were created out of a preference for privacy and anonymity (Nakamoto, 2008). While wallet addresses (i.e., hexadecimal codes) are public, the true identity of the person behind the code is oftentimes not (Rhue, 2018). Hence, even if there were a legal basis for legal action, it would be nearly impossible in practice to pin down the individuals behind hexadecimal codes and hold them accountable (see also Fisch, 2019). Third, a potentially even more severe practical problem of prosecuting questionable token offerings is the dilemma between national enforcers and globally distributed online platforms. The globally distribution of most token-based online platforms poses a problem to national enforcers. There are no international institutions that would clarify cross-border enforcement and, even if they ultimately exist at some point in the future, it is not clear whether the prosecution in potentially more than a hundred countries justifies the underlying value in dispute (Dobrautz and Klebeck, 2019). These arguments illustrate that there are severe obstacles to the *ex post punishment of biased signals*.

Overall, low entry barriers to the ICO market, the *ex ante* viability of sending biased signals, and the lack of *ex post* punishment of biased signals may provide incentives for token issuers to send biased signals in an environment characterized by increasingly fierce competition for growth capital. In this situation, signaling may not work efficiently enough to match investors and entrepreneurs, and a *moral hazard in signaling* is likely to occur (Houben, 2002). Simply put, if investors cannot discriminate between biased and truthful signals, not sending a biased signal would result in a competitive disadvantage in the form of, for example, a comparatively lower funding amount. Hence, entrepreneurs plausibly have, at least in the short term, an incentive to send biased signals at the expense of their investors.

More generally, moral hazard occurs when transacting parties share risk, and one party bears the cost of the risk taken by another party (Hölmstrom, 1979; Mirrlees, 1999; Rogerson, 1985). In the context of IPOs, Hurt (2004) defines moral hazard as an "*incentive created by any agreement between parties for one party to actively engage in dubious behavior that will either reward the party or at least not create loss for the party*." The role of moral hazard has been discussed extensively in the IPO and VC literature. At a conceptual level, Hurt (2004) discusses the role of company founders being in a disunion between the company's long-term objective (acquiring growth capital) and self-interested short-term goals (exit options). Hurt (2004) also argues that the sheer amount of private wealth that could be appropriated by manipulating the fundraising campaign is tempting for many founders, which may create severe moral hazard.[9]

In the context of token offerings, moral hazard might even be more pronounced for at least three reasons. First, entry barriers are relatively low, hence entrepreneurs driven by short-term goals (private wealth) might be more prone to attempt an ICO rather than crowdfunding, VC, or an IPO.[10] Second, the opportunity to trade tokens provides even faster exit opportunities for founders, which again reduces the access barriers to substantial increases in private wealth. Third, there is high overall industry uncertainty about the prospects of token-based business models Natarajan et al. (2017) and evidence that entrepreneurs are aware of the hot-market opportunities that they try to exploit (Drobetz et al., 2019). Hence, ventures may be tempted to maximize their funding amount as long as this opportunity lasts.

3.4. Consequences of moral hazard

This section conceptually explores the potential consequences of moral hazard in the ICO context by deriving two overarching hypotheses.

The first hypothesis is that the indulgence in moral hazard is profitable for token issuers in the presence of dispersed investors with limited information exchange, known in this study as the *asymmetric information hypothesis*. This conjecture is based on classical monitoring and coordination problems among dispersed investors (Becht et al., 2003; Berle and Means, 1932; Jensen and Meckling, 1976). Dispersed investors lack the incentive to monitor ventures and have difficulties coordinating monitoring tasks and information exchange with each other. In this environment, dispersed investors are not able to ex ante identify manifestations of moral hazard, and ventures thus have a financial incentive to indulge in moral hazard.

Monitoring problems arise because dispersed investors are individually too small to have an economic incentive to monitor ventures. They oftentimes lack the financial and technological knowledge to adequately value a technical business model, and the cost of creating such a knowledge base would exceed the potential benefits, given the limited investment amount by individual investors (Cohney et al., 2018). This problem is even more pronounced in token offerings because token issuers often disclose relatively little information, increasing the necessary effort on the part of a potential monitor (Kaal and Dell'Erba, 2017; Kastelein, 2017). Monitoring problems are further aggravated in the ICO context because developers of token-based platforms oftentimes work independently and are geographically dispersed (Malinova and Park, 2018). Initial evidence shows that the monitoring function exercised by aggregator platforms such as *ICObench* is not sufficient (Boreiko and Vidusso, 2018). This might be explained by the fact that these platforms do not thrive to create new information, but simply consolidate publicly available information.

Coordination problems arise for a number of reasons. First, the prevailing preference for privacy among many investors in token-based assets makes it difficult to overcome the pseudo-anonymous market structure in order to be able to coordinate information exchange among investors (Fisch, 2019; Nakamoto, 2008). Second, a lack of incentives preempts the creation of coordinating agents. Even if a compensation structure for coordinators existed, it is unclear who should get delegated coordinating power, how coordinators would be elected or determined, and how it could be ensured that they are not captured by industry. Third, there are a number of practical issues. Given global investor outreach in token offerings, there are language barriers and investors may have different motives (e.g., financial vs. non-financial (see Lipausch, 2018) and hence different requirements to monitoring and coordinating.

[9] Similarly, research analysts covering a deal may be tempted to report a biased view on the company's prospects (see, also for the empirical evidence, Michaely and Womack (1999)). The role of biased analysts might indeed be even more pronounced in the context of ICOs given the incentive of bounty programs in many ICOs (Howell et al., 2018).

[10] Note that the empirical evidence of moral hazard in the context of IPOs is mixed due in some part to the difficulty to unambiguously quantify manifestations of moral hazard in practice (Li and Masulis, 2004; Ljungqvist and Wilhelm Jr, 2003).

Overall, monitoring and coordinating problems among dispersed investors in token offerings limit the ability to reduce informational asymmetries and constrain agency costs. They make it less likely for investors to *ex ante* detect manifestations of moral hazard, making it in turn profitable for token issuers to indulge in moral hazard.

Hypothesis 1. Manifestations of moral hazard are profitable for token issuers in the presence of dispersed investors with limited information exchange ("*asymmetric information hypothesis*").

The second hypothesis is that the indulgence in moral hazard might eventually backfire on token issuers when dispersed investors are able to pool information, which is labeled the *crowd-learning hypothesis*. Given monitoring and coordination problems, the listing of the token after the token offering marks an important event for dispersed investors. When the token is listed, supply and demand dynamics start to form an equilibrium price; that is, a fair price given all the available information about the venture. As such, the token exchange listing performs the coordination function that dispersed investors fail to perform on their own.[11] In particular, the token price on exchange platforms should reflect the aggregate wisdom of the crowd which, through the readily-observable market price, becomes available to all dispersed investors (Li, 2016). If the venture has indulged in moral hazard, investors learn through the equilibrium price that the venture is overvalued because of biased signals sent during the token offering. As a result of this learning, investors will adjust their valuations (for a seminal model of the value implication of moral hazard with revenue-sharing contracts, see Bhattacharyya and Lafontaine, 1995). Overvaluation entails downward price adjustments as soon as trading begins. This view is supported by the finding that about four out of ten ventures experience negative returns on their first day of trading (Momtaz, 2020b). Furthermore, downward price pressure may actually deter potential after-market investors, which might eventually affect long-term platform success when network effects do not occur because of negative initial returns. This is consistent with Bergemann and Hege (1998) who provide a theoretical model to show that entrepreneurial projects may fail prematurely if agency costs are too high.

Hypothesis 2. Manifestations of moral hazard backfire on token issuers as soon as dispersed investors can pool information ("*crowd-learning hypothesis*").

In summary, the incentives for a token-based venture to indulge in moral hazard may vary over its life-cycle, depending on the ability of its dispersed investor base to aggregate the wisdom of the crowd, as illustrated by Fig. 2. Because of monitoring and coordination problems among dispersed investors, manifestations of moral hazard may be profitable up to a point (*asymmetric information hypothesis*). The critical event that changes the incentives to indulge in moral hazard is plausibly the listing of the token, after which supply and demand dynamics form a fair token price that is readily observable to dispersed investors. After the listing, manifestations of moral hazard are reflected in overvalued tokens; hence, investors can start to adjust their valuations, with detrimental consequences for these ventures (*crowd-learning hypothesis*). The implications are twofold: Under the *asymmetric information hypothesis*, ventures that indulge in moral hazard might be able to enter the market earlier and raise higher funding amounts. Under the *crowd-learning hypothesis*, these ventures should experience lower initial returns and are more likely to fail in the long term.

4. Method

4.1. Empirical setting: data sources and sample

By now, a number of databases have emerged that provide data related to token offerings, although their scopes often differ substantially (for a discussion, see Boreiko and Sahdev, 2018). A recent tendency among researchers leans toward the *ICObench* database because it also provides comprehensive information about team and deal characteristics that have been shown to be important drivers behind ICO performance indicators (e.g., Howell et al., 2018; Momtaz, 2018). An important advantage of the *ICObench* dataset is that it also provides data on some failed projects, hence mitigating to some extent a potential survivorship bias which is present in many databases. The consequences of this potential bias are discussed in Section 6.4.

The available data on *ICObench* is by no means sufficient for the purpose of this paper. For example, important but missing information includes historic token prices, time-to-market measures, social and human capital characteristics, as well as proxies for technological capabilities. Therefore, the *ICObench* data is supplemented with hand-collected data from a number of sources such as *Coinmarketcap* and *Crunchbase*, social networks such as *LinkedIn* and *Twitter*, *Github* repositories, and project websites. It is interesting in itself to note that there is only relatively little overlap between the *ICObench* and *Coinmarketcap* databases, which reduces the sample size. This is further discussed in Section 6.4. Therefore, the full *ICObench* sample will continue to be used whenever historic token prices that can only be obtained from *Conmarketcap* are not required for the analyses.

Furthermore, an important observation during the sampling process is that nowhere near all ICOs publish whitepapers. In fact, I find less than half of all ICOs during the sampling period did so. To make sure that this is not due to an oversight of the data sources, I perform a manual web search for every case in which a whitepaper is missing. More to the point, missing whitepapers may indicate a sample selection bias if ICO projects *choose* not to publish one. Therefore, this study samples ICOs with and without whitepapers to be able to correct for the potential sample selectivity in Section 5.3.

A final restriction is that only *utility tokens* are included in the sample. Utility tokens are most often issued in ICOs, and they are

[11] Moreover, the market price for tokens can be viewed as performing a monitoring function as well. Poor management entails token price depreciation, which reduces the funds available for platform development by retained tokens and hinders network effects. As such, market prices may discipline poorly performing agents.

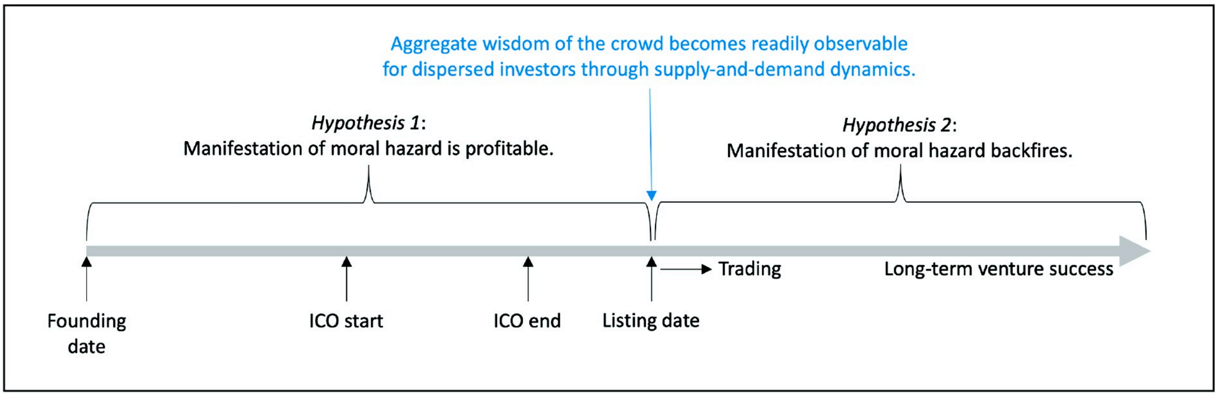

Fig. 2. Life-cycle of token-based ventures and overview of hypotheses.

distinct from crypto-tokens and security tokens because they are not subject to asset and securities laws (Howell et al., 2018). Also, including crypto-tokens and security tokens would imply the need to control for the regulation of the jurisdictions to which the projects have opted in, which is difficult as regulatory standards are still in the process of being constructed (Dobrautz and Klebeck, 2019; Zetzsche et al., 2018). Failure to control for regulation, however, would constitute a substantial omitted variable problem. This methodological challenge can be overcome through a focus on utility tokens. Moreover, because of the lack of regulatory oversight, behavior associated with moral hazard might be more pronounced in ICOs which only issue utility tokens. Therefore, utility tokens are the primary focus in this study.

Overall, *ICObench* provides an international sample of 2,130 ICOs for my sample period, i.e. between August 2015 and June 2018. Thereof, only 1,043 ICOs have whitepapers. A further reduction of my sample stems from the requirements that (i) the sample ICOs issued utility tokens and (ii) all necessary controls, as described below, are available from the other data sources I use (e.g., *LinkedIn* and *Coinmarketcap*[12]). This leads to a final sample of 495 ICOs.

4.2. Variables

4.2.1. Dependent variables

This study analyzes the determinants of an extensive number of dependent variables that can broadly be categorized into *market performance indicators* (time-to-market, funding amount, and fundraising technique) and *aftermarket performance indicators* (token-holder returns, token volatility, delistings, and project failures).

4.2.1.1. Market performance indicators

Time-to-market. Time-to-market is considered alongside two important dimensions; time-to-funding and time-to-listing.

Time-to-funding. Time-to-funding is defined as the number of days between a company being founded and the beginning of the token offering. This is a commonly-used variable in entrepreneurial finance studies to proxy for a start-up's pre-market efficiency employed in the context of many markets such as IPOs (Khurshed, 2011) and VC (Gompers and Lerner, 2004). The variable is obtained by merging several data sources. The company's founding date comes from either the projects' websites, or *Crunchbase*, or the CEOs' *LinkedIn* profiles and the time of the token offering is available from *ICObench*. Given the time-to-event structure of this variable, I employ a reciprocal hazard rate model.

Time-to-listing. Time-to-listing is defined as the number of days between the end of the token offering and the date a token is listed on a token exchange platform. Data to construct the variable comes from *ICObench* (date of the end of the token offering) and *Coinmarketcap* (date of the first day of trading). Time-to-listing is particularly interesting in the context of token offerings because it proxies for the endogenously determined time period in which entrepreneurs create a viable exit option for themselves. As for the time-to-funding variable, a reciprocal hazard rate model is also used here.

Funding amount. Funding amount (in USD) is log-transformed to account for positive skewness. This is the main dependent variable used in Fisch (2019), whose followed in the construction of the variable. However, the data come from *ICObench*. Because some projects only accept cryptocurrency in exchange for their token, I have to convert all funding amounts in currencies other than USD to USD based on the quoted exchange rate on *Coinmarketcap* at the beginning of the token offering period. It is important to clarify that this variable corresponds to the gross proceeds raised in a token offering before advisor fees and an adjustment for bounty programs. It is thus representative of the attractiveness for investors and is therefore well suited to the purpose of this study. The main specification estimates the model using OLS, although the results are robust to employing GLM and ROBUST estimation techniques (cf., Fisch, 2019).

[12] Note that the data that comes from *Coinmarketcap* is sampled for the extended period from August 2015 to April 2019 in order to achieve maximum coverage.

Fundraising technique: price discrimination × duration. This dependent variable is coded as an interaction variable based on an indicator that is equal to one if the token issuer decreased the price during the offering period, and the duration of the token offering (in days). It is a key variable because it proxies for whether a token issuer 'cleans out under the demand curve' at high economic cost, as explained below, which might be indicative of a manifestation of moral hazard. Hellmann and Puri (2002) argue that early investors require a discount for assuming higher risk and signaling venture quality to the market. This is how many empirical and theoretical papers rationalize the relatively deep discounts to earlier rather than later investors in entrepreneurial financing efforts (see, for example, Gompers and Lerner, 2001). In contrast, some token offerings are structured in a way that fundamentally breaks with this market expectation. So-called *Initial Supply Actions* (*ISAs*) are designed to start with a relatively high price and then lower the token price until all investors are reached (for a brief discussion, see Momtaz, 2019b). One rationale behind employing such a fundraising technique is that entrepreneurs aim to raise the maximum amount of funding possible at all costs, thereby penalizing their earliest investors, which might send an adverse signal to potential subsequent investors. The data come mainly from *ICObench* and is supplemented with data from the projects' whitepapers, websites, and blogs to gather information about price discrimination. Because most prices are quoted in terms of *ETH*, *BTC*, and/or *LTH* (for an overview of the relative distribution of exchange currencies, see Momtaz et al., 2019), I converted all prices into USD using historic prices from *Coinmarketcap*.

4.2.1.2. Aftermarket performance indicators

Initial returns. Initial returns are considered in different variations. Here, I examine unadjusted, market-adjusted, and binary initial returns. Initial returns are the returns on the first day of trading. These are used in several studies in the context of token sales (e.g., Momtaz, 2018; Kostovetsky and Benedetti, 2018; Felix, 2018; Drobetz et al., 2019; Dittmar and Wu, 2018) as they reflect the market reaction of investors when the token is publicly traded for the first time. The data come from *Coinmarketcap*. *Average unadjusted returns* are computed as the price difference at the end relative to the beginning of the first trading day:

$$\overline{R} = \frac{1}{n}\sum_{i=1}^{n}\frac{P_{i,1} - P_{i,0}}{P_{i,0}} \tag{1}$$

where $P_{i,0}$ denotes the first price when trading begins on the first day a token i is listed and $P_{i,1}$ denotes the closing price on the first trading day. This return estimate might be biased on days when the whole token market experiences significant price changes. To deal with this possibility, I also calculate *average abnormal initial returns*, $\overline{AR}$, as follows:

$$\overline{AR} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{P_{i,1} - P_{i,0}}{P_{i,0}} - \sum_{j=1}^{n}\frac{MC_{j,1}}{\sum_{j=1}^{n} MC_{j,1}}\cdot\frac{P_{j,1} - P_{j,0}}{P_{j,0}}\right] \tag{2}$$

where I subtract the market capitalization-weighted market return from the raw return defined in Eq. (1). The market capitalization-weighted market return is computed as the sum of the returns of all j cryptocurrencies listed on the day when token i starts trading, weighted by the market capitalization of all j tokens at the end of the day ($MC_{j,1}$) relative to the whole market capitalization $\left(\sum_{j=1}^{n} MC_{j,1}\right)$. Finally, *binary initial returns* are measured using a dummy variable for whether the initial return, adjusted or unadjusted, was positive (coded "1") or negative (coded "0") to ensure the robustness of the continuous return measures to outliers.

Token volatility. Token volatility is measured using the realized-variance approach (Momtaz, 2020b), using historic price data from *Coinmarketcap*. Volatility is measured during the first month of trading to reflect investors' initial uncertainty about the venture quality.

Delistings and project failure. Delistings are defined as events when a token is delisted from at least one exchange platform, but continues to be traded on other platforms.

Project failures are defined as events in which tokens are delisted from all exchange platforms, which effectively represents a company's death. The data for both, delistings and project failures, are obtained from the largest 26 token exchange platforms.

4.2.2. Independent variable: manifestation of moral hazard in signaling through an informational exaggeration bias

To capture the *exaggeration bias* in whitepapers, I use a linguistic AI-based algorithm which follows Hu and Liu (2004). The main advantage over other text-mining algorithms is that it learns from amplification words (i.e., very, too, hugely, etc.), which are important features for the measurement of exaggeration. Specifically, the degree of exaggeration, ζ, is defined as a function of neutral, positive, negative, amplification, and negation words, weighted by the overall whitepaper word count:

$$\zeta = \frac{\sum\left[x_i^0, x_i^{amplifier} + x_i^+ * (-1)^{\sum\left(x_i^{negator}\right)}, x_i^{amplifier} + x_i^- * (-1)^{\sum\left(x_i^{negator}\right)}\right]}{n} \tag{3}$$

Each word in each sentence is first classified as being neutral (x_i^0), positive (x_i^+), negative (x_i^-), amplifiers ($x_i^{amplifier}$), or negators ($x_i^{negator}$) according to the Hu and Liu (2004) dictionary. However, other dictionaries are also employed for robustness checks. Only positive and negative words have a value of > 0 and < 0, respectively. Neutral words have no value but affect word count per sentence, n. Positive and negative words are then weighted according to their degree of amplification, where amplifiers are defined as $x_i^{amplifier} = \frac{1}{n-1}$. Hence, an amplification word has a higher weight if the sentence is relatively short. The weighted word is then multiplied by (-1) to the power of the sum of negators. Finally, the total sum is scaled by the maximum ζ to make sure the exaggeration bias lies between

− 1 and 1. In Fig. 3 (see Empirical results section), a histogram of the exaggeration bias shows that the variable is normally distributed around the mean of 0.25 in the population of whitepapers. Fig. 4 (see Empirical results section) examines the exaggeration bias over time, showing some evidence that the variance of the bias increases gradually.

4.2.3. Control variables

Controls for confounding effects are selected based on prior research on ICOs (e.g., Fisch, 2019; Howell et al., 2018; Momtaz, 2018), which draws on related literatures such as crowdfunding (e.g., Mollick, 2014; Ahlers et al., 2015; Vismara, 2016; Anglin et al., 2018), venture capital (e.g., Hellmann and Puri, 2002; Gompers and Lerner, 2004), and IPOs (e.g., Ljungqvist and Wilhelm Jr, 2003; Ritter and Welch, 2002). Based on Fisch (2019), I include sets of controls for (i) the technological capabilities of the venture, (ii) other venture characteristics, and (iii) the characteristics of the token offering. While there may be more candidate variables to control for confounding effects, the focus in this study is on those that have been shown to have a significant effect on venture success, with others being omitted (cf., Fisch, 2019).

4.2.3.1. Control variables: proxies for technological capability

ERC20 (dummy). ERC20 refers to the underlying blockchain technology, namely *Ethereum*, on which ventures can build their platform. There are other available technologies (e.g., *NEO* and *Waves*) and a venture can develop its own technology, but *Ethereum* is by far the most prominent solution. A recent study estimates that about 88% of all tokens are based on the ERC20 standard (Momtaz et al., 2019). ERC20 defines a set of immutable governance terms and technical standards, which might signal value-enhancing system stability and interoperability across platforms. In keeping with this, ERC20 is associated with several ICO success outcomes such as the funding amount (Fisch, 2019), token liquidity (Howell et al., 2018), time-to-market, returns, and project failure (Momtaz, 2018). ERC20 is defined as an indicator variable coded "1" if a platform is based on ERC20, and "0" otherwise. Data come mainly from *ICObench* and are supplemented with hand-collected data in certain cases.

Github defect fixes (log). Another variable that is linked to a venture's technical capability and is associated with venture success is the number of defect fixes to source code posted on *Github* (Fisch, 2019). Following Fisch (2019) based on Syer et al. (2015), I reconstruct the number of defect fixes that ICO investors could observe at the start of the token offering. This was done by analyzing all commits' descriptions for each venture's commit history on Github for key words such as "fix/ed/s", bug/s", "defect/s", and "patch/s/ed/es".

4.2.3.2. Control variables: venture characteristics

Ratings. To capture the effect of investor perception of specific ICO attributes, I obtain data on analyst ratings from *ICObench*. Most

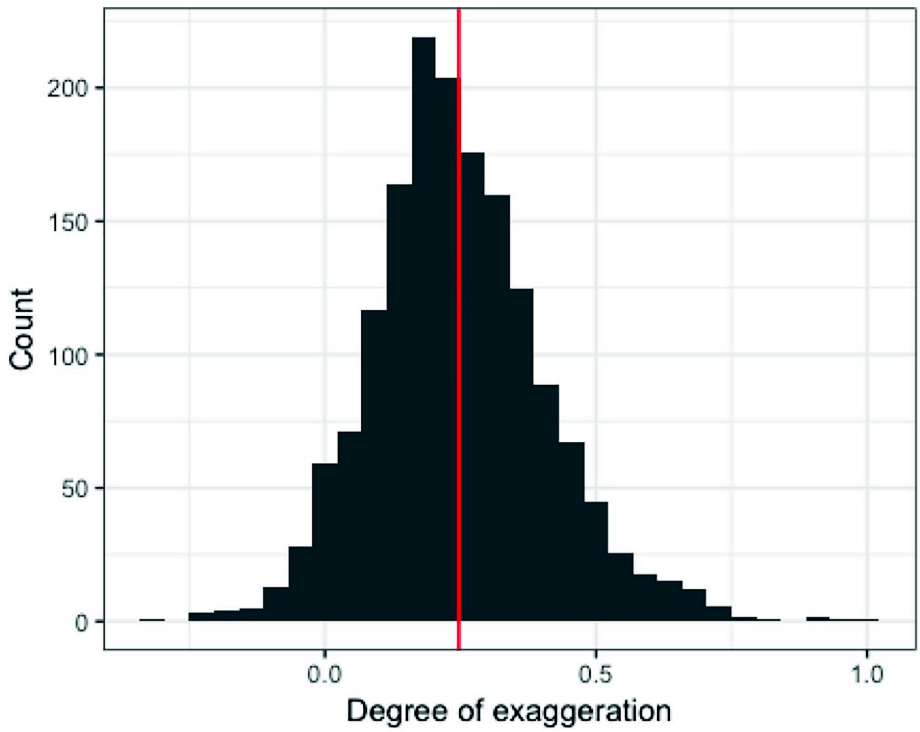

Fig. 3. Histogram of informational exaggeration (ζ) in all whitepapers of completed token offerings published between April 2015 and November 2018.

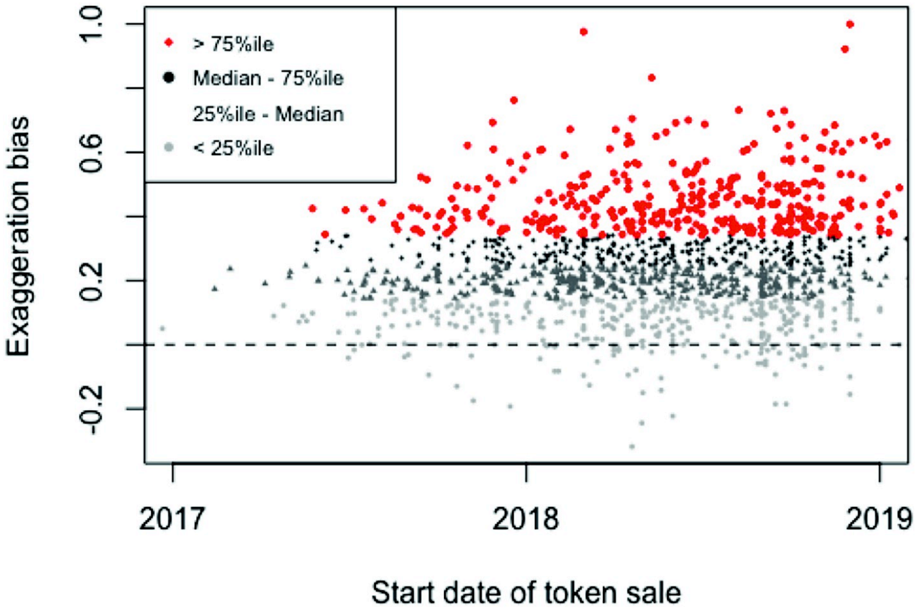

Fig. 4. Informational exaggeration (ζ) over time.

token sales are covered by more than 20 independent analysts, hence the average of all analyst ratings is taken along the three dimensions. The values range from 0 ("low quality") to 5 ("high quality"). These ratings cover the quality of the management team (*"management rating"*), the company's vision (*"vision rating"*), and the company profile (*"profile rating"*). Momtaz (2018) shows that management rating and profile rating are positively related to ICO success. In contrast, the vision rating has a negative effect because highly visionary projects are more likely to fail. Importantly, Florysiak and Schandlbauer (2018) show that these expert ratings are determined by easy-to-extract whitepaper information such as team size, investor restrictions, and social media channels. Hence, in the context of this study, it is important to condition on these ratings in order to isolate the effect the exaggeration bias has on the market and aftermarket performance of token offerings.

Twitter. Due in large part to the disintermediated nature of token offerings, ventures rely to a great extent on direct communication channels to their dispersed investor base. Social media sites such as Twitter have been shown to have a strong effect on the fundraising success of blockchain-based ventures (Fisch, 2019; Kostovetsky and Benedetti, 2018). For example, Bartov et al. (2017) find that Twitter activity predicts earnings announcements, which is a test of the ' wisdom of the crowd', which might be an explanation of how Twitter helps reduce informational asymmetries among dispersed investors. Based on this prior work, I capture Twitter activity by the log of the number of Tweets associated with the token offering, which is collected from the ventures' Twitter profiles.

CEO crypto-experience (years). An important human capital characteristic that may drive fundraising success is CEO experience (Ahlers et al., 2015). In fact, recent research shows that *related* industry experience is driving the positive relationship between experience and firm value because it is associated with the skills and expertise that are important for a specific company (Drobetz et al., 2018). In keeping with this finding, studies of token offerings have also started to include proxies for a CEO's crypto-experience (An et al., 2018; Momtaz, 2018). I construct the CEO crypto-experience proxy from hand-collected *LinkedIn* data, where the variable is defined as years of crypto-experience until the start of the token offering. In robustness checks, I test the alternative specification using an indicator variable approach, in which CEO crypto-experience takes a value of "1" if the entrepreneurial CEO had at least one crypto-related project prior to founding the focal venture.

CEO loyalty. CEO loyalty is defined as the cumulative work experience in years divided by the total number of jobs over the career of CEOs. To construct the variable, labor market biographies are retrieved from the CEOs' professional network profiles, such as *LinkedIn*. The rationale behind conjecturing that CEO loyalty might affect market outcomes in entrepreneurial finance comes from experiments in social psychology. They show that loyalty emerges automatically within randomly assigned groups, with the effect being more pronounced for relatively important groups (such as investors from the perspective of the CEO) (for a review, see Cohen, 2008). Loyalty might influence a CEO's utility gain and hence his or her optimal decision making (Akerlof and Kranton, 2000, 2005). In the context of the asymmetric information-plagued token offerings, loyalty's positive impact on CEOs' individual utilities might partially eliminate agency problems because shirking decreases relatively loyal CEOs' utilities. Indeed, Momtaz (2020a) shows that CEO loyalty is positively related to funding amount, operational efficiency, and long-term success, suggesting that CEO loyalty signals venture quality.

US and EU location (dummies). Geographical determinants may have an effect on token offerings (Huang et al., 2018), although it is *ex ante* plausible that location plays a lesser role in blockchain-based crowdfunding than in other entrepreneurial financing methods due to the central role of internet mediation (Mollick, 2014). Therefore, as in Fisch (2019), I include location-fixed effects for the US and the EU, where the locational status is determined either by venture disclosure in the whitepaper, their project website, or the CEO's primary country of residence based on his or her *LinkedIn* profile.

4.2.3.3. Control variables: characteristics of the token offering

Market sentiment. Cryptocurrency markets are extremely volatile (Bianchi, 2018; Liu and Tsyvinski, 2018). This gives ventures an incentive to time the market, affecting several features in this study (e.g., time-to-market, funding amount, returns, etc.). Indeed, Drobetz et al. (2019) show that ventures time the market according to overall sentiment and bitcoin prices in a way that aims to avoid negative sentiment episodes. To control for this confounding effect, I control for market sentiment proxied by the price change in *BTC*, which is the largest cryptocurrency in terms of market capitalization and trading volume, over the period of the token sale. Historic prices are obtained from *Coinmarketcap*.

Minority investor protection. Arguably many entrepreneurs are attracted to utility token offerings as a method to acquire growth capital because of the low degree of regulation (Zetzsche et al., 2018). On the other hand, investors require higher financial incentives in the absence of strong corporate governance and legal investor protection (Dissanaike et al., 2020; Drobetz and Momtaz, 2019; Gompers et al., 2003; Porta et al., 1998). This trade-off may be affected by the legal investor protection in a given jurisdiction. For example, ventures in a low-protection country may need to offer more incentives for potential investors to partake in the offering, compared with ventures in high-protection countries. To capture this level effect at country level, I control for the *minority shareholder protection* index from Porta et al. (1998). The minority shareholder protection index is particularly suited to the context of token offerings, given that ICO investors are often small and therefore rely on legal protection. The minority shareholder protection index is matched to the ventures' jurisdictions when available; otherwise, it is matched to the CEO's country of residence (taken from *LinkedIn* profiles).

Token supply (log). In contrast to fiat currency, a token is, in principal, infinitely divisible, so the number of tokens issued in a token offering carries little meaning per se. However, Fisch (2019) finds a positive relation between token supply and funding amount. He rationalizes this finding using behavioral finance theory. Investors in the crypto market may be relatively more drawn to lottery-type tokens as they can be purchased at relatively lower costs per token but there is a chance, however small, of delivering astronomically high returns. Hence, high token supply may be a proxy for low price per token, which attracts investors. Data on token supply are provided mostly by *ICObench* and *ICOalert*, and are hand-collected from whitepapers and project websites when necessary.

Whitepaper word count (in 1000 words). Word count has ambiguous effects in crowdfunding. While it may reduce asymmetric information by providing more relevant information (Cohney et al., 2018; Moss et al., 2018), it may also reduce precision (Davis et al., 2017). It may also have little or no effect at all in the context of token sales if investors do not trust voluntarily disclosed information (Blaseg, 2018; Florysiak and Schandlbauer, 2018). To control for these potential confounders, and to be consistent with Fisch (2019) who finds a positive effect, I include the number of words in each whitepaper (in thousands).

Investor restrictions. Many token offerings impose investor restrictions such as whitelists or KYC (Know-Your-Customer) processes, which reduces the pool of potential investors and increases the fundraising time (Blaseg, 2018). On the other hand, investor restrictions ensure that ventures know who invests in their platform, and they may help to create long-term venture-investor relationships (Li and Mann, 2018). To capture these potential influences, a proxy for investor restrictions is included, which is coded as an indicator variable equal to "1" if at least one restriction is in place, and "0" otherwise. Data to construct the variable come form *ICObench*.

Country restrictions. Several ventures exclude investors from specific countries from participating in the token sale to avoid regulatory scrutiny. Investors from the US (29%) and China (18%) are most often subject to such restrictions (Momtaz et al., 2019). While such restrictions may reduce the pool of potential investors, they also protect ventures from potential future legal disputes later on as well as delays in the fundraising process due to reasons related to regulatory compliance (Dobrautz and Klebeck, 2019; Zetzsche et al., 2018). Therefore, an indicator variable is included, which equals "1" if investors from at least one country are excluded from the token sale, and "0" if all investors can participate.

5. Empirical Results

5.1. Summary statistics

Table I shows summary statistics for the full sample of 495 token offerings. The sample is drawn from a population of 2131 token offerings between August 2015 and November 2018, of which 1043 ventures published whitepapers.

5.1.1. Dependent variables

The mean (median) venture conducted the token offering after 598 days or 20 months (312 days or 10.5 months). The mean (median) token-offering period was 264 days or 9 months (31 days or 1 month). The funding amount in terms of gross proceeds (before advisor and listing fees) was $15.1 m for the average venture, and $5.8 m for the median. As per the distribution of this variable, the first-quantile venture raised $1.5m, which compares with $ 18m raised by the third-quantile token issuer. The unadjusted and adjusted initial returns are 8.2% and 7.6% for the mean and 2.6% and 3.3% for the median listing, suggesting that investors in the aftermarket react positively to the majority of token listings. These are notably high figures given that tokens already gain significant value already during the period immediately after the offering ends and before the token is listed (Kostovetsky and Benedetti, 2018). Nevertheless, the binary variable suggests that 57.4% of all tokens experience a price appreciation on the first day of trading, which implies that more than 4 out of 10 tokens are actually overpriced. Average volatility during the initial trading period is 7.7% for the mean and 2.8% for the median. Interestingly, more than every fifth venture is delisted (21%) and 13% of all ventures fail completely.

5.1.2. Independent variables

Interestingly, the measure of the exaggeration bias, ζ, is almost normally distributed over all whitepapers, as Fig. 3 illustrates. The mean (vertical line in the figure) is 0.247, whereas the median is 0.233. ζ was actually scaled to be in an interval of $[-1; 1]$, so that zero

Table I
Descriptive statistics.

Variable	Mean	St. dev.	Q1	Median	Q3
Panel A: sample overview					
# Token sales in population	2131				
# Token sales with whitepaper	1043				
# Token sales with complete information	495				
Panel B: dependent variables					
Time-to-funding (in days)	598	1596	173	312	672
Time-to-listing (in days)	93	209	22	42	71
Token sale duration (in days)	264	1083	27	31	49
Gross proceeds (in $ mil)	15.1	28.1	1.5	5.8	18.0
Initial returns (*unadjusted*)	0.082	0.256	−0.045	0.026	0.190
Initial returns (*adjusted*)	0.076	0.274	−0.088	0.033	0.205
Initial returns (*binary, unadj.*)	0.574	0.495	0	1	1
Money left on the table (in $ mil)	1.1	7.0	−0.1	0.0	0.9
Volatility (1st trading month)	0.077	0.247	0.015	0.028	0.049
Delisting	0.21	0.41	0	0	0
Failure	0.13	0.34	0	0	0
Panel C: main independent variable					
Degree of exaggeration (ζ)	0.247	0.261	0.143	0.233	0.341
Panel D: proxies for technological capabilities					
ERC20 (dummy)	0.803	0.398	1	1	1
GitHub (log of # defect fixes)	1.33	1.87	0	0	0
Panel E: venture characteristics					
Management rating	1.916	1.879	0.000	2.000	3.800
Vision rating	1.943	1.894	0.000	2.000	3.900
Profile rating	3.167	1.027	2.400	3.100	4.000
Twitter (log of # tweets)	7.151	2.178	5.215	6.529	7.852
CEO crypto-experience (dummy)	0.432	0.495	0	0	1
CEO loyalty (avg. tenure in years)	2.5	1.9	1.3	2.0	3.0
Location: US (dummy)	0.25	0.43	1	0	0
Location: EU (dummy)	0.41	0.49	1	1	1
Panel F: characteristics of the token offering					
Market sentiment (in %)	0.03	0.09	−0.05	0.04	0.15
Minority investor protection	3.31	0.32	2	3	4
Token supply (log)	20.01	2.55	10.54	18.77	19.90
Word count (in thousand)	7.70	4.61	3.92	6.90	10.69
Country restrictions (dummy)	0.48	2.51	0	0	0
Investor restrictions (dummy)	0.26	0.44	0	0	1

would correspond to no bias. Given that even the first-quantile token issuer has a significantly positive ζ of 0.143 (compare to third-quantile ζ of 0.341), there is a systematic positive bias or "euphemism" in the entire sample. Fig. 4 plots the ζ score over time. The plot illustrates that the exaggeration bias may have increased over time (or at least its variance), indicating that it may be necessary to adjust standard errors for heteroskedasticity in the multivariate tests.

5.1.3. *Control variables*

Proxies for technological capabilities: About 80% of all tokens are based on the ERC20 standard. The natural log of GitHub defect fixes is 1.33 for the mean and 0 or the median, which is again similar to (but a little lower than) the sample statistics in Fisch (2019).

Venture characteristics. For the expert ratings (from 0 = weak to 5 = strong), the management team is on average rated 1.92 (median = 2.0), with standard deviation of 1.88. Similarly, the vision rating average (median) is 1.94 (2.0) with standard deviation of 1.89. Only the profile rating is clearly higher (mean = 3.17, median = 3.1, standard deviation = 1.0), although the variance is clearly smaller, suggesting that 'window dressing' might be very pronounced among token issuers. The average venture has log-Tweets of 7.2, with a median of 6.5. On average, 43% of all CEOs had prior crypto-experience when they started the token sale. CEO loyalty is 2.5 years for the mean and 2.0 years for the median. Of all token offerings, 25% and 41% were conducted by U.S. and European ventures, respectively.

Characteristics of the token offering. The market sentiment variable shows that token issuers 'time the market,' which is consistent with Drobetz et al. (2019), as the mean and median are positive. Porta et al.'s (1998) minority shareholder rights index has a mean (median) of 3.3 (3.0) in this sample. The logged token supply is 20.0 for the mean and 18.8 for the median. The average (median) whitepaper is about eight thousand (seven thousand) words long. Interestingly, 25.8% of all token offerings impose investor restrictions and 48.1% even exclude investors from at least one country.

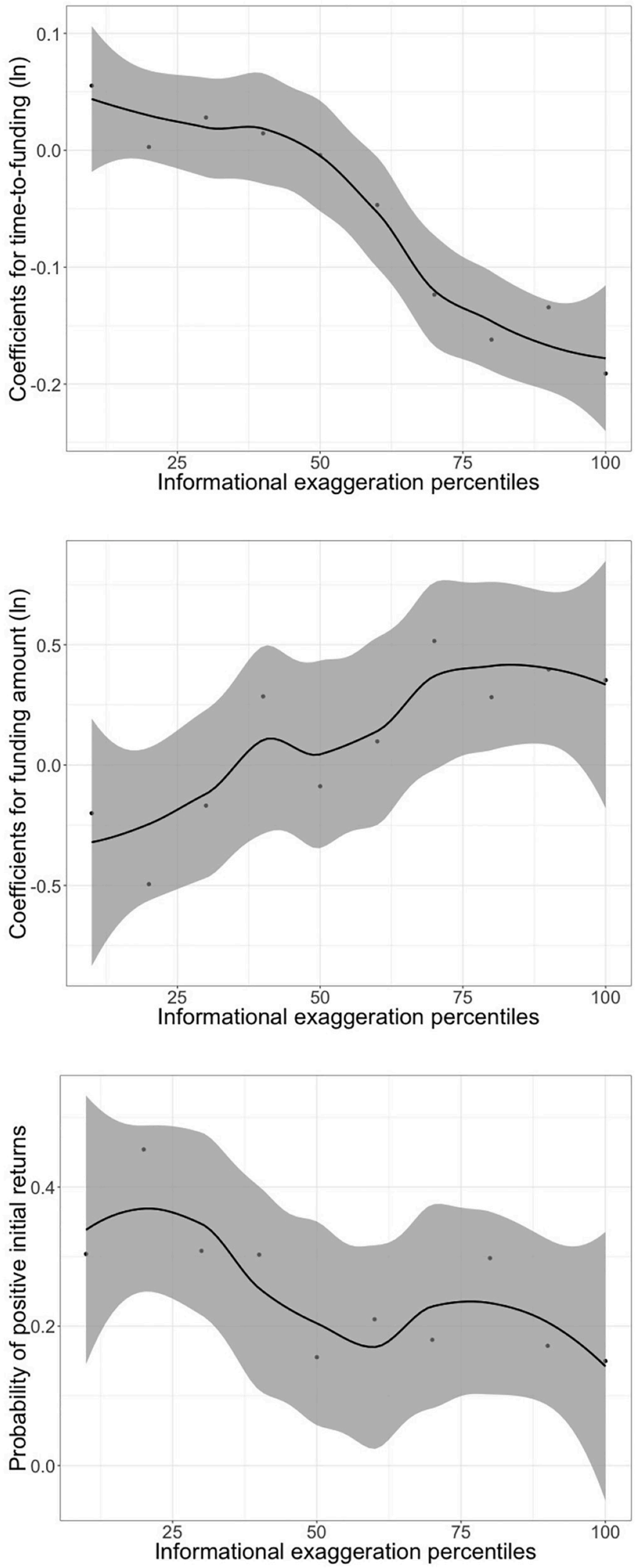

Fig. 5. This figure shows the coefficients of informational exaggeration (ζ) scores from quantile regressions with smoothed lines and confidence bands for the time-to-funding (log.) (graph at the top), the funding amount (log.) (graph in the middle), and the probability of positive initial returns (graph at the bottom) univariate models with time-fixed effects.

To ensure that multicollinearity among these variables is not a problem, I check both pair-wise correlation coefficients and variance inflation factors (VIFs). With all correlations below 0.7 and all VIFs below 5, collinearity in my sample does not exceed commonly-agreed thresholds (Leitterstorf and Rau, 2014), and hence I conclude that collinearity is not a concern in the sample.

5.2. Preliminary univariate evidence

To provide some preliminary statistical evidence on the relationship between informational exaggeration and select market and aftermarket performance variables, I present graphical evidence in Fig. 5. Specifically, I plot the relationship for three dependent variables that are key to my theory: time-to-funding, funding amount, and probability of positive initial returns. The three graphs are based on univariate quantile regressions that regress the dependent variable on decile-based dummies for the extent of informational exaggeration (and time fixed effects). The coefficients for each of the ten dummies are then taken to fit a smooth line along with confidence bands. This allows for a continuous representation of the relationship between informational exaggeration and the three dependent variables at each percentile.

The graphs in Fig. 5 show that the univariate evidence is consistent with both the asymmetric information hypothesis and the crowd-learning hypothesis. The graph at the top shows that the time-to-funding is a decreasing function of informational exaggeration. That is, ventures that are at the higher end of informational exaggeration can raise funds in less time. Further, the graph in the middle indicates that high informational exaggeration also increases the funding amount. The preliminary evidence for these two market performance variables is supportive of the asymmetric information hypothesis: Manifestations of moral hazard are profitable for ventures (here in the sense of less time-to-market and higher funding amount) as long as dispersed investors cannot pool information. However, the graph at the bottom of Fig. 5 suggests that manifestations of moral hazard backfire as soon as investors can pool information. The graph shows that the probability of positive initial returns decreases in informational exaggeration. This is evidence in support of the crowd-learning hypothesis. The token price pools the information distributed over the dispersed investor base, whereby investors can re-assess their initial venture valuation and sell tokens of exaggerating ventures, which creates downward price pressure. Overall, the preliminary evidence supports my overall theory, but multivariate analyses that control for confounding effects are necessary to draw more robust inferences.

5.3. First-stage: sample selectivity correction

One concern in the ICO market is that not all projects publish whitepapers, which might indicate selectivity to some extent. In fact, less than half of all ICOs documented on *ICOBench* published whitepapers during the sample period. This might be due to a sample selection bias if projects choose not to disclose information because they are not developed enough or have fraudulent intentions, among other motives. Neglecting sample selectivity might bias my subsequent analyses. Therefore, I conduct a Heckman (1979) two-stage correction for the sample selection bias. The first step involves estimating a probit model for the probability that a project publishes a whitepaper, given some project quality characteristics. Table II reports the marginal effects of the probit model. The quality of both, the management team and the ICO profile are significantly (p-value < 10% and < 1%, respectively) and positively related to the likelihood of a whitepaper being issued. The second step uses the density and distribution functions from the first stage to compute *inverse Mills ratios*. The inverse Mills ratios are included in the subsequent analyses to control for sample selectivity. I also experiment with other model specifications, which expand the set of control variables. The issue with an extensive model is that variables such as Twitter activity, location choices, token supply, investor and country restrictions are all endogenous in nature, and may thus bias the density and distribution functions obtained to construct the control variable for the second stage. For this reason, the parsimonious specification that uses only exogenous expert ratings as shown in Table II is preferred. However, the subsequent analyses do not change substantially with less parsimonious models either.

5.4. Main results

5.4.1. Time-to-market

Columns 1 and 2 of Table III present results from reciprocal hazard rate models (RHRMs) with time-to-funding and time-to-listing

Table II
Heckman first-stage to correct sample selectivity.

Dependent variable: whitepaper published (binary)		
Management rating	−0.0967*	(0.0585)
Vision rating	0.0156**	(0.0640)
Profile rating	0.2017***	(0.0318)
Constant	−0.8583***	(0.0941)
# obs.	2131	
AIC	2850.2	

* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

as the dependent variables, respectively. Both columns include all 495 observations and the full set of control variables.[13]

Model 1 shows that the exaggeration bias reduces the time to funding significantly by 169 days (mean = 598 days) for the highest biased token offerings relative to unbiased ones. However, it is *ex ante* ambiguous whether this is because investors are fooled by euphemized whitepapers or whether this is by endogenous choice on the part of the token issuers (e.g., they may want to exploit a window of opportunity in a hot market instead of waiting with the offering until they really have a ready-to-market platform). Interestingly, the exaggeration bias also has a negative effect on the time-to-listing, which is unaffected by investor demand and purely determined by the issuer. High exaggeration is associated with a reduced time-to-listing of 8 days (mean = 32 days). This suggests that the overall time-to-market is lower if the exaggeration bias is relatively high, which is at least to some extent because of choice by the exaggerating entrepreneur.

For the control variables, columns 1 and 2 indicate that neither proxy for technological capabilities (ERC20 and GitHub defect fixes) is significantly related to the time to market. However, most venture characteristics at least determine the time to funding. Interestingly, good management teams raise funds later, whereas highly visionary and strong-profile issuers are able to start the token offering earlier. Strong managers also list their tokens later, which might be suggestive of them being more thorough or careful. High Twitter activity and previous CEO crypto-experience help funds to be raised earlier, although the effects are clearly smaller in magnitude than those of the expert ratings. CEO loyalty prolongs the time to funding substantially, which is in line with the hypothesis that more loyal CEOs are also more prudent (Momtaz, 2020a). Location seems to determine time-to-market to a lesser extent; only the U.S. dummy is weakly significant in model 1.

Among the characteristics of the token offering, only three seem to have a significant impact on the time to market. A whitepaper's word count slightly prolongs the time to funding, as do investor restrictions. This can be attributed to the fact that the creation of and compliance with whitelists and KYC processes is very time-consuming. However, country restrictions reduce the time-to-market as they help avoid effort related to regulatory filings and compliance in some countries (Dobrautz and Klebeck, 2019).

Finally, it is noteworthy that the inverse Mill's ratio is significant in model 1, suggesting that sample selectivity would bias the results in the absence of the Heckman (1979) procedure.

5.4.2. *Funding amount and technique*

Column 3 of Table III presents OLS regression results with funding amount (log) as the dependent variable. Standard errors are adjusted for heteroskedasticity and clustered by quarter-years and issuer country (Howell et al., 2018). The exaggeration bias is significantly positively related to the funding amount (p-value < 1%), suggesting that investors fail to identify ventures that are more susceptible to moral hazard in signaling.

An important reason why exaggerating ventures raise more funds is shown in column 4. These ventures are more likely to increase the offering period and decrease the token price at the same time. Price discrimination penalizes early investors who expect a steep discount for taking higher risks and signaling venture quality to the market (Hellmann and Puri, 2002). Although this tactic, known as Initial Supply Actions (ISAs) (see, for an introduction, Momtaz, 2019b), may help to maximize the funding amount by reaching investors with a lower willingness to pay, it may backfire when disappointed early investors abandon the platform. Hence, the combined evidence in models 3 and 4 shows that exaggerating ventures are able to extract more gross proceeds by exploiting early investors.

The proxies for technological capabilities suggest that only the log-number of GitHub defect fixes is significantly related to the funding amount. More GitHub fixes are associated with higher gross proceeds. Among the venture characteristics, only Twitter activity and a U.S. location are significant; as expected, both increase the funding amount. For the characteristics of the token offering, I find that only token supply has a positive effect, while country restrictions reduce the acquired growth capital. Interestingly, the longer the duration of the token offering, the lower the proceeds. This may result from unsuccessful ventures remaining in the market for longer. Overall, the results are mostly consistent with Fisch (2019), although there are some minor differences (e.g., word count being not significant) that might stem from the different samples (here: mainly *ICObench*, in Fisch (2019): *CoinSchedule*) and the conditioning on exaggeration in signaling.

5.4.3. *Initial returns and volatility*

The results so far show that exaggerating ventures tap the market faster, list their tokens earlier, and are able to raise more funding but only by exploiting their early investors. This section begins to uncover whether investors learn about the exaggeration bias and how they react.

If investors learn about the exaggeration bias, they might start to abandon the platform as soon as they can, which is effectively when the token is listed. This should put downward price pressure on the token, which likely coincides with increased volatility levels (Lee et al., 2002). Specifically, the token price of exaggerating ventures should fall relative to truthful ventures, and their volatility should initially be higher because there is more crowd ambiguity about the true platform value. This is exactly what the results in Table IV show. The table presents OLS regression analyses for unadjusted, market-adjusted, and binary initial returns on the day a token is listed, as well as token price volatility over the first month of trading. Standard errors are adjusted for heteroskedasticity and clustered by quarter-years, with inverse Mill's ratios also included.

Models 1 and 2 show how exaggeration, technological capabilities, venture characteristics, and characteristics of the token offering

[13] Note that one concern is that time-to-funding is affected by unobserved heterogeneity. This would require a random-effects time-to-event model (for a methodological paper on this, see Momtaz, 2020c). However, in the context of ICOs, I find in unreported results that unobserved heterogeneity (at least related to ICO firms' countries) is minimal.

Table III
Reciprocal hazard rate (RHR) and OLS models of time to market, and funding amount and technique.

	Time-to-funding		Time-to-listing		Gross proceeds (log)		ICO duration × Price decrease	
	RHR	(p-val.)	RHR	(p-val.)	Coef.	(SE)	Coef.	(SE)
Exaggeration bias (ζ)	−169***	(0.00)	−8**	(0.03)	0.218***	(0.049)	0.041**	(0.018)
Proxies for technological capabilities:								
ERC20 (dummy)	−161	(0.24)	−38	(0.30)	0.525***	(0.114)	0.215	(0.132)
Github (log of # defect fixes)	5	(0.28)	−3	(0.35)	0.105**	(0.062)	0.215	(0.133)
Venture characteristics:								
Management rating (StDev)	7***	(0.01)	8*	(0.08)	0.198	(0.139)	0.054	(0.044)
Vision rating (StDev)	−92***	(0.01)	−6	(0.12)	0.242	(0.158)	−0.061	(0.062)
Profile rating (StDev)	−258*	(0.09)	2	(0.37)	0.064	(0.105)	0.148	(0.209)
Twitter (log of # tweets)	−19**	(0.04)	−4	(0.16)	0.059*	(0.039)	−0.001	(0.011)
CEO crypto-experience	−24***	(0.00)	0	(0.49)	0.100	(0.170)	−0.001	(0.015)
CEO loyalty	140***	(0.00)	2	(0.19)	0.005	(0.009)	0.009	(0.020)
Location: US (dummy)	41*	(0.10)	−1	(0.52)	0.520*	(0.350)	−0.001	(0.011)
Location: EU (dummy)	−14	(0.15)	1	(0.29)	0.150	(0.181)	−0.001	(0.011)
Characteristics of the token offering:								
Market sentiment (in %)	10	(0.19)	−2**	(0.04)	0.030	(0.089)	−0.003**	(0.001)
Minority investor protection	3	(0.14)	−1*	(0.09)	0.017	(0.014)	−0.004	(0.005)
Token supply (log)	32	(0.43)	1	(0.68)	0.028**	(0.014)	−0.120	(0.096)
Word count (in thousand)	11*	(0.09)	3	(0.55)	0.082	(0.098)	−0.120	(0.096)
Investor restrictions (dummy)	278***	(0.01)	57*	(0.08)	−0.036	(0.031)	−0.120	(0.096)
Country restrictions (dummy)	−93***	(0.01)	−47***	(0.00)	−0.047*	(0.025)	−0.075	(0.092)
Duration (in days)					−0.001**	(0.000)	−0.075	(0.092)
Constant					1.790	(2.508)	0.697	(0.618)
Inverse Mill's Ratio	Yes*		Yes		Yes		Yes*	
Time fixed effects (quarter-years)	Yes		Yes		Yes		Yes	
No. Observations	495		302		495		201	
LogLik	1762		385					
Adjusted R^2					0.232		0.096	
p-value	0.000		0.017		0.006		0.044	

Note: Yes* indicates significant Inverse Mill's Ratio at least at the 5% level.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

impact unadjusted and market-adjusted initial returns, respectively. Relative to unbiased ventures, tokens of exaggerating ventures drop by more than 5% on the first trading day. In fact, the binary specification in model 3 indicates that exaggerating entrepreneurs have an 8% higher probability of decreasing in value. The evidence is most indicative of the conjecture that investors learn this. It is less clear, however, how investors learn about it. Two potential mechanisms seem plausible. First, investors may learn about the true platform value from management's behavior after the token offering ends and before the token is listed (e.g., through the use of proceeds, the achievement of milestones, and investor relations and communication). Second, drawing on crowd-learning theories (Kremer et al., 2014), investors may learn about true platform value through trading with other investors until an equilibrium price is found.

Some empirical support for the latter channel comes from model 4 in Table IV. Model 4 regresses token volatility during the first month of trading on the determinants. Volatility levels are significantly higher when a moral hazard in signaling occurs (p-value < 1%). This suggests that the uncertainty about true platform value is higher when a venture does not report truthfully. Interestingly, the significant coefficient on the exaggeration bias vanishes over longer volatility periods. The results are insignificant, as hypothesized, and are hence not reported. However, this finding suggests that investors learn about the true platform value from trading with other investors. Overall, the results in Table IV support the interpretation that exaggerating information backfires as investors learn about true platform value in the aftermarket.

For the proxies of technological capabilities (ERC20 and GitHub defect fixes), I find that both are positively related to initial returns, albeit insignificantly. However, venture characteristics seem to be important determinants of initial returns. Both, management ratings and CEO crypto-experience are positively related to initial returns at least at the 5% significance level, whereas returns decrease in vision and profile ratings (p-value < 1%). The negative effect of vision ratings has been explained by the fact that highly visionary projects are more difficult to be implemented and are hence more likely to fail eventually (Momtaz, 2018). The negative effect on profile ratings is consistent with the hypothesis that token issuers indulge in "window dressing" which might also inflate investor expectations. Looking at the volatility regressions in model 4, the effects are reversed. This is expected because positive signals should reduce uncertainty, whereas negative signals likely induce uncertainty. Volatility decreases in management ratings, while it increases in vision and profile ratings. The characteristics of the token offering are also strong determinants of initial returns and volatility; positive market sentiment helps boost returns, and token supply (log) is also positively related to initial returns as well as to volatility. This supports the conjecture expressed in Fisch (2019) that investors may have a preference for lottery-like tokens (low value but high upside potential, which is reflected in high volatility levels). Furthermore, country and investor restrictions are also

Table IV
OLS regressions for returns and volatility.

	Initial return (unadjusted)		Initial return (market-adj.)		Initial return I(Return)>0		Volatility (1st month)	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Exaggeration bias (ζ)	−0.0504**	(0.0232)	−0.0569**	(0.0275)	−0.0806***	(0.0269)	0.0137***	(0.0039)
Proxies for technological capabilities:								
ERC20 (dummy)	0.0708	(0.0464)	0.0560	(0.0414)	−0.0281	(0.1045)	−0.1455	(0.1172)
Github (log of # defect fixes)	0.0012	(0.0011)	0.0012	(0.0012)	0.0018	(0.0042)	−0.0003	(0.0010)
Venture characteristics:								
Management rating (StDev)	0.1116***	(0.0124)	0.1061***	(0.0213)	0.0954	(0.0755)	−0.0584***	(0.0169)
Vision rating (StDev)	−0.1084***	(0.0124)	−0.095***	(0.0205)	−0.0920	(0.0711)	0.0628***	(0.0220)
Profile rating (StDev)	−0.1989***	(0.0458)	−0.2143***	(0.0610)	−0.1302	(0.1465)	0.1288*	(0.0769)
Twitter (log of # tweets)	0.0031	(0.0038)	0.0033	(0.0042)	−0.0051	(0.0096)	−0.0011	(0.0054)
CEO crypto-experience	0.0068***	(0.0013)	0.0044***	(0.0014)	−0.0067	(0.0054)	−0.0008	(0.0010)
CEO loyalty	−0.0196**	(0.0082)	−0.0086	(0.0144)	0.0134	(0.0121)	−0.0053	(0.0037)
Location: US (dummy)	−0.0028	(0.0030)	−0.0027	(0.0029)	−0.0010	(0.0021)	−0.0009	(0.0014)
Location: EU (dummy)	0.0004	(0.0013)	0.0005	(0.0013)	−0.0011	(0.0026)	−0.0006	(0.0035)
Characteristics of the token offering:								
Market sentiment (in%)	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0003***	(0.0000)	0.0000	(0.0000)
Minority investor protection	0.0002	(0.0003)	0.0002	(0.0003)	0.0005	(0.0009)	0.0007*	(0.0004)
Token supply (log)	0.0041**	(0.0017)	0.0040**	(0.0017)	0.0028*	(0.0014)	0.0019***	(0.0007)
Word count (in thousand)	0.0002	(0.0004)	0.0002	(0.0004)	−0.0000	(0.0001)	0.0001	(0.0001)
Country restrictions (dummy)	0.0262***	(0.0051)	0.0211***	(0.0066)	0.0324***	(0.0092)	−0.0178*	(0.0106)
Investor restrictions (dummy)	−0.2414***	(0.0388)	−0.1858***	(0.0433)	−0.5990***	(0.0570)	−0.0653***	(0.0221)
Constant	−0.5171**	(0.2053)	−0.4180*	(0.2457)	0.2026	(0.6446)	0.4974*	(0.2980)
Inverse Mill's Ratio	Yes*		Yes*		Yes		Yes*	
Time fixed effects (quarter-years)	Yes		Yes		Yes		Yes	
No. Observations	302		302		302		300	
Adjusted R^2	0.1509		0.1572		0.0597		0.0661	
p-value	0.031		0.023		0.094		0.043	

Note: Yes* indicates significant Inverse Mill's Ratio at least at the 5% level.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

significant predictors of initial returns and volatility. Note that the inverse Mill's ratio is significant in three out of four models.

5.4.4. Delistings and failure

The results so far suggest that investors are attracted to token issuers that exaggerate in the first place, but then sell the token once they learn about the bias. This section explores the long-term consequences of the occurrence of moral hazard in signaling. Specifically, the way in which exaggeration bias affects delistings and project failure is examined. Table V reports the results from a right-censored linear probability model (rcLPM) as well as the corresponding marginal effects from a probit estimation.

The main result is that exaggerating ventures are significantly more likely to be delisted from at least one token exchange platform and eventually fail. Among the proxies for technological capabilities, ERC20 is associated with a positive probability of delisting, while GitHub defect fixes reduce the probability of project failure. For the other characteristics, only CEO loyalty and country restrictions affect the probability of delistings (negatively). However, several venture characteristics are strong predictors of failure. Good management and profile ratings reduce the probability of failure, while high vision ratings increase it. Perhaps surprisingly, CEOs with more crypto-experience are more likely to fail. One explanation is that many CEOs had prior projects that failed, which might send a negative signal. However, more research on the identities of CEOs, developers, and investors is required to arrive at a definite conclusion. Two other venture characteristics, CEO loyalty and U.S. location, are negatively related to project failure. For the characteristics of the token offering, minority shareholder rights have a surprisingly positive impact on the failure rate, as do country restrictions. Although the models account for right-censoring, samples over longer time horizons are required to establish how invariant these determinants ultimately are.

5.5. Robustness checks

5.5.1. Robustness checks pertaining to the measure of the exaggeration bias

The empirical results suggest that a moral hazard in signaling occurs in token offerings, which investors are not able to detect as such and act accordingly right from the beginning. Further, investors seem to learn about the manifestation of the moral hazard only when the market dynamics of supply and demand become readily observable once token trading begins. Hence, the trading start is plausibly highly informative of investor learning. To shed more light on the relation between the exaggeration bias and initial returns on the first day of trading, I test different level-effect models. Specifically, I regress market-adjusted initial returns on the full model 2 in Table IV, with the change that the continuous measure of the exaggeration bias is replaced by a binary variable equal to one if $\zeta < 40\%$ile, as well as >40%ile, >60%ile, and >80%ile, respectively. Consistent with the interpretation of investor learning, I find a

Table V
Linear probability models with rhs censoring for delistings and project failure (incl. MEs from probits).

	Exchange delisting			Project failure		
	Coef.	(SE)	Marginal effect	Coef.	(SE)	Marginal effect
Exaggeration bias (ζ)	0.0271***	(0.0046)	0.0293	0.0720***	(0.0183)	0.0753
Proxies for technological capabilities:						
ERC20 (dummy)	0.0288**	(0.0120)	0.0305	−0.0493	(0.0480)	−0.0499
Github (log of # defect fixes)	−0.0027	(0.0024)	−0.0019	−0.0093**	(0.0040)	−0.0061
Venture characteristics:						
Management rating (StDev)	0.0048	(0.0093)	0.0052	−0.0550*	(0.0302)	−0.0621
Vision rating (StDev)	−0.0037	(0.0099)	−0.0021	0.0609**	(0.0301)	0.0553
Profile rating (StDev)	0.0201	(0.0455)	0.0187	−0.1090***	(0.0357)	−0.0843
Twitter (log of # tweets)	−0.0001	(0.0005)	−0.0009	0.0004	(0.0007)	0.0001
CEO crypto-experience	0.0010	(0.0015)	0.0012	0.0085**	(0.0035)	0.0098
CEO loyalty	−0.0071**	(0.0030)	−0.0078	−0.0300**	(0.0127)	−0.0286
Location: US (dummy)	−0.0055	(0.0049)	−0.0050	−0.0094*	(0.0061)	−0.0107
Location: EU (dummy)	−0.0034	(0.0039)	−0.0039	−0.0052	(0.0087)	−0.0063
Characteristics of the token offering:						
Market sentiment (in%)	0.0056	(0.0062)	0.0044	0.0016	(0.0074)	0.0029
Minority investor protection	−0.0003	(0.0004)	−0.0002	0.0004	(0.0009)	0.0005
Token supply (log)	0.0037	(0.0046)	0.0029	0.0025*	(0.0013)	0.0037
Word count (in thousand)	0.0009	(0.0013)	0.0006	−0.0007	(0.0001)	−0.0001
Country restrictions (dummy)	−0.0013***	(0.0003)	−0.0014	−0.0295	(0.0217)	−0.0311
Investor restrictions (dummy)	0.0066	(0.0233)	0.0055	0.1414***	(0.0550)	0.0901
Constant	0.0894	(0.0839)		0.1203	(0.2643)	
Inverse Mill's Ratio	Yes			Yes		
Time fixed effects (quarter-years)	Yes			Yes		
No. Observations	302			302		
Adjusted R^2	0.0942			0.1038		
p-value	0.058			0.010		

Note: Yes* indicates significant Inverse Mill's Ratio at least at the 5% level.
* p<0.1.
** p<0.05.
*** p<0.01.

monotonically decreasing relationship between the four models. Model 1 ($\zeta <$ 40%ile) indicates that truthfully reporting ventures outperform exaggerating ones by 23% (significant at the 1% level) when trading begins. In contrast, exaggerating ventures experience downward token price pressure that increases in the relative level of exaggeration ($\zeta >$ 40%ile: −5.5%, $\zeta >$ 60%ile: −8.3%, $\zeta >$ 80%ile: −17.8%). The results are not tabulated but are available upon request.

Additionally, the results are robust to two more ad-hoc tests. First, I vary the measurement of the exaggeration bias in several ways to be consistent with other studies employing similar linguistic AI techniques (e.g., Bartov et al., 2017). In particular, the results are qualitatively the similar if I reduce the relevance of amplification words and if the exaggeration is simply defined as a sentiment score by taking the difference between one and the ratio of negative over total words in a whitepaper using several dictionaries (see, for the latter approach, Bartov et al., 2017). Second, the results do not materially change if each tail of the exaggeration bias is winsorized by 1% or 5%.

5.5.2. *Robustness checks pertaining to dependent variables*

5.5.2.1. Initial returns. Given the relevance of initial returns for this study (see Sections 5.2 and 5.4.3) and the sensitivity to different market benchmarks and computation methods (MacKinlay, 1997), market-adjusted initial returns are calculated in several ways. Specifically, the market capitalization-weighted adjustment index is replaced only with BTC and ETH prices, the market-adjustment technique is replaced with an OLS market model, and the event window is widened from the first day of trading gradually to the first week of trading. For the sake of brevity, these results are not tabulated, however, they are consistent with the set of main results documented herein.

5.5.2.2. Error terms. Another potential concern stemming from Fisch's (2019) insight is that error terms in regression analyses with the funding amount as the dependent variable may deviate from a normal distribution. This may result in a violation of the OLS assumptions, which might bias the results. To address this concern, I perform a generalized least squares (GLS) estimation instead of the OLS procedure (see Anglin et al., 2018 for an application in the context of crowdfunding). In line with Fisch (2019), the results from the GLS model are very similar to those of the OLS model (hence a tabulation of the results is omitted). Furthermore, in an effort to assure that the results are not biased by non-normal error terms, all models are re-estimated using the GLS procedure. All results are robust to this modification.

5.5.3. Robustness checks pertaining to independent variables

5.5.3.1. Fundraising goal. Prior work uses the fundraising goal or a dummy for the existence of such a goal as a control variable (Ahlers et al., 2015; Fisch, 2019; Mollick, 2014). If a venture caps the funding amount, this effectively reduces the maximum funding, rendering the funding amount a poor proxy for funding success or venture quality. Indeed, Fisch (2019) finds a positive relationship between funding goal and funding amount (using lags of both). To address this issue, I gather data on funding goals, which are referred to, in the ICO context, as soft and hard caps. Using the logged hard caps as a control, the existence of a positive correlation with the funding amount is confirmed, but the main results are robust. Also, logged soft cap has a similar but much weaker effect. Because not all ventures have funding goals, a dummy variable (=1 if there is a funding goal) is used to utilize the full sample. Again, the main results remain unchanged, as in Fisch (2019).

5.5.3.2. Patents. Patents might also affect the analyses in principle. However, I find that only 29 of the sample ventures have filed for a patent, and all applications were still pending at the time of the token offering. When a dummy variable for the existence of a pending patent application is included, the parameter estimates are insignificant throughout all model specifications. It is ex ante not clear whether the insignificance is because patents are not valuable in token-based ventures with public source code (see, for a comprehensive discussion, Fisch, 2019) or simply because of a lack of statistical power. Either way, the main results remain qualitatively unchanged. It is interesting to note, however, that in the top-quartile of exaggerating ventures, none had a patent application.

5.5.3.3. Ad-hoc robustness checks (not reported). To further assess the robustness of the results, a number of ad-hoc robustness tests is conducted. First, the robustness of the results to the inclusion of additional independent variables such as CEO education (coded as dummy variable for the categories no college, college, and post-graduate), professional experience of managers and advisors in years (log.), and various macro-economic indicators (such as GDP and stock market development) is confirmed. Second, as a more systematic approach to rule out a bias from omitted variables, I include granular country- and industry-fixed effects. While this rules out any confounding effect from omitted variables at the country and industry level, it also substantially reduces the variation in the data. Therefore, the main models reported in the above Empirical results sections are built on less granular fixed effects (for example, dummies for country-fixed effects based on the US, the EU, and the rest of the world). Nevertheless, the main results remain qualitatively similar when I include the more granular fixed effects. Overall, this exercise rules out a country- and industry-related omitted variable bias.

6. Discussion and Concluding Remarks

6.1. Discussion of the main results

Token issuers systematically exaggerate information disclosed in technical whitepapers. In an efficient market for entrepreneurial finance, entrepreneurs would truthfully report their projects' prospects and investors would pick those projects with the highest expected net present value. When investigating why the market for token offerings is less efficient, there are a number of (partly temporary and partly permanent) frictions that facilitate the manifestation of a moral hazard in signaling. Permanent frictions are that entrepreneurial signals are not difficult to imitate (e.g., only a few projects have marketable products, most signals are based on an entrepreneur's vision for a product) and are very inexpensive to transmit (i.e., they are disseminated over social media). A temporary friction is that there are, as yet, no functioning institutional forces in the market for token offerings that could verify entrepreneurial signals and penalize ventures sending false signals. An additional important feature is that competition for growth capital in the market for token offerings is increasingly fierce, and most issues are structured in such a way that the entrepreneur can only tap the market once (i.e., the maximum supply of tokens is fixed). The relative inexpensiveness to create and disseminate (even false) signals, paired with the fact that token issuers know they have only 'one shot' at acquiring the desired funding amount, creates an overall welfare-detrimental incentive to exaggerate. This is effectively a moral hazard in signaling.

Somewhat surprisingly, investors fail to identify the occurrence of the moral hazard initially, or they are at least not able to correctly identify exaggerating entrepreneurs. Exaggerated projects attract substantially more funding in significantly less time, suggesting that the ' wisdom of the crowd' is bounded. The natural next question is why investors fail to see through the exaggeration bias. Although it is difficult to provide a definitive answer to a counterfactual, there are some potential explanations on the part of the investors. One explanation is that token offerings require technological knowledge that not every micro-investor might possess (Fisch, 2019). Another reason is that token offerings are knowledge-intensive but currently more than three token offerings take place each day (Momtaz et al., 2019), which suggests that investors may not have enough time to accumulate the necessary knowledge. Yet another potential reason is that investors are plagued by a Fear Of Missing Out (' FOMO') in a ' hot market' that might induce them to irrationally ignore the exaggeration bias. However, this paper shows how entrepreneurs exploit their investors by conducting their token offerings for a longer period of time and gradually lowering the token price, whereby they 'clean out under the demand curve.' This, however, penalizes early investors who paid a higher price, although they had a higher risk and signaled venture quality to the market (Hellmann and Puri, 2002).

The efficiency of the token market improves in the aftermarket. Investors learn about the true platform quality when they trade with each other. The learning process is observable in the trading data. Over the first month after a token starts trading, the volatility (i.e., investor uncertainty) is higher for exaggerated projects, and gradually decreases as the learning continues. Disappointed investors dump tokens once trading begins, resulting in plummeting token prices. Investors abandon exaggerated projects, which are more likely to fail eventually. The finding that investors identify exaggerations only in the aftermarket rather than during the actual token offering illustrates the cost of informational asymmetries in entrepreneurial finance: Small investors may not be able to acquire sufficient information to accurately gauge a project's true value, and some projects might take advantage of this.

6.2. Contributions of this study

This study contributes to the literature on asymmetric information and signaling in entrepreneurial finance and, specifically, in token offerings. While signaling has been proposed as a conceptual framework in equity crowdfunding (Ahlers et al., 2015; Vismara, 2016, 2018) and token offerings (Fisch, 2019), the literature lacks a critical perspective. This study shows that, under certain circumstances, a moral hazard in signaling may occur that impedes the overall efficiency of the market for entrepreneurial finance. Specifically, this study feeds the nascent body of research on token sales in the empirical (e.g., Fisch, 2019; Howell et al., 2018; Momtaz, 2018, 2019a; Kostovetsky and Benedetti, 2018; Dittmar and Wu, 2018; Lyandres et al., 2018) and theoretical (e.g., Li and Mann, 2018; Chod and Lyandres, 2018) entrepreneurial finance literature with a critical perspective.

In particular, it contrasts with the view in Fisch (2019) (based on Spence, 1973) that assumes that entrepreneurs can effectively and efficiently signal their quality to investors. In the context of token sales, signaling is very cost-efficient, easy to imitate, and it is inexpensive to send false signals due to a lack of penalizing institutions. Given fierce competition for growth capital and the fact that token offerings are often designed in a such way that ventures can raise funds for a specific project only once, this may create an incentive to send biased signals to increase the expected funding amount, which effectively constitutes a moral hazard in signaling.

Sending biased signals may in fact exacerbate informational asymmetries. In the logic of the classic Akerlof (1978) model, the moral hazard in signaling may even entail a 'market for lemons.' Investors cannot distinguish between valuable and less valuable projects and are hence only willing to bid the average value of the two types. The valuable project then has an incentive to signal its quality in order to create a 'separating equilibrium,' in which both projects receive the fair funding. In the presence of a moral hazard in signaling, the low-quality project has an incentive to exaggerate so that the high-quality project is relatively worse off. If market participants fail to eliminate the inefficiency, the moral hazard may cause market failure by crowding out valuable projects. This consequence may also apply to other forms of entrepreneurial finance if they are characterized by low levels of intermediation, as is explained next. This environment fosters a moral hazard, which may exacerbate asymmetric information, and might eventually lead to a 'market for lemons' (Akerlof, 1978; Chod and Lyandres, 2018).

The market for token offerings may illustrate that the trend toward increasing disintermediation in entrepreneurial finance may be welfare-detrimental overall. Perfect disintermediation may result in market failure in the absence of a rule-setting institutional framework, or of institutional investors who have the resources and incentives to screen and monitor entrepreneurs, as explained above. From a theoretical perspective, a solution to this dilemma may come from an added layer of intermediation. Currently, most token sales are structured in a such way that the maximum token supply is fixed. This implies that entrepreneurs can only tap the market once, fostering a moral hazard. Instead, the introduction of underwriters in token sales may reduce the margin of value to be shared between entrepreneurs and investors, but it would also transform token sales into 'sequential games.' The underwriter's reputation would repeatedly be at stake in each token sale, reducing the incentive to succumb to moral hazard. As such, underwriter-backed token sales may profit from a 'certification effect', hence crowding out perfectly disintermediated token sales.

6.3. Practical implications

A number of practical implications emerge from the findings and theoretical implications. For ventures, the existence of systematic exaggeration in information disclosure poses a dilemma. On the one hand, the opportunistic choice to exaggerate has negative long-term consequences associated with disappointed investors. On the other hand, if ventures resist exaggerating, they may raise less growth capital. In fact, it is possible (and beyond the scope of this study) that, in the absence of exaggeration, the attracted investor attention might be insufficient for network effects to impact, so that, everything else being equal, a low-quality but exaggerating venture may eventually outperform a high-quality and truthful venture.

Besides policy-making, there may be ways under the ventures' control that could provide a solution to this dilemma. Creating trust is at the center of such an effort (Rhue, 2018). For example, ventures may organize personal investor meetings or, as some have already begun to, hold live FAQ sessions on *Youtube* channels. Another way is to get ' external certification' (Officer, 2007). This may be achieved through the due diligence of reputable auditors, VC-backing, or through other intermediaries that have the skills and incentives to reduce asymmetric information.

Furthermore, the token economy brings new features to entrepreneurial finance, implying the need for ventures to develop novel skill sets. Perhaps the most relevant novelty is the immediate liquidity of tokens through token exchange platforms, which provide a transparent measure of the venture value any time, and are observable to all investors. Ventures are exposed to the risk of token price depreciation, which poses a threat to platform survival. The other reason is that most platforms retain tokens to award developers and finance growth initiatives, which may be detrimentally affected by token price depreciation. All this implies a necessity to install a function for investor relations and communication at a scope that does not exist within traditional ventures.

For investors, this study implies that the existing signals, such as expert ratings and those associated with technical capabilities (e.g., source code), are not sufficient to discriminate between high- and low-quality projects. Therefore, investors are well-advised to look for alternative signals such as VC-backing or measures related to trust. Despite the critical view presented in this paper and the overall perception (for example, estimates are that about 85% of all token sales are scams (cited in Malinova and Park, 2018)), investors largely seem to identify major 'red flags' as many token offerings fail to receive any funding in the first place (Blaseg, 2018). Also, despite the obvious downside potential (about four out of ten tokens decrease in value after the listing), the average return to investors is still positive because of a few 'superstar tokens' (Momtaz, 2020b).

For policy-makers and regulators, token offerings pose a high risk to investors (e.g., Clayton, 2017). The results herein confirm this view and hint at a severe regulatory vacuum: In the absence of penalties for sending false signals, a moral hazard in information disclosure occurs and investors are not able to sufficiently reduce informational asymmetries on their own. This suggests the need for policy-making focusing on retail investor protection. Policy-making is also due because, as I have explained above, the ICO market may turn into a 'market for lemons.' In terms of policy-making, two approaches seem promising. First, policy-makers may consider policies that promote the creation of informal institutions of trust (Rhue, 2018). This may be achieved, for example, by providing incentives for reputable players in the ' traditional economy' to enter the token economy. Second, regulators may provide different types of formal institutions. One type is a national regulation that holds entrepreneurs accountable for biasing signals of venture quality. While these institutions exist in most countries, enforcement is challenging as resources and knowledge lag behind the market evolution. Also, it is not clear to what extent globally distributed platforms can be bound to one jurisdiction (Dobrautz and Klebeck, 2019). Therefore, voluntary opt-in approaches as successfully practiced in the case of wallet provider *CoinBase* seem promising. Another type of formal institution necessary to confine moral hazard in token offerings pertains to the creation of organizations for supra-national policy-making. This is necessary, as many token ventures operate on globally-distributed platforms that span across national borders.

6.4. Limitations

The market for token offerings is still at a very early stage and therefore data available for research have limitations, which might affect the generalizability of the findings presented in this study. Specifically, there are at least two threats to external validity. First, it is common knowledge that data aggregators such as *ICObench* eliminate certain, mostly fraudulent token sales from their records *ex post*. This introduces a survivorship bias that cannot be remedied with publicly available information (see also Blaseg, 2018). To mitigate the issue, I compared data sources (*ICOalert* and *coingecko*), and cross-referenced data obtained from different sources such as project websites, whitepapers,and professional network profiles. However, the findings can only be safely interpreted locally for the sample that survives. This is an issue in *all* empirical studies of ICOs. One way to avoid this problem in the future is to take snapshots of the available data at regular time intervals (for example, weekly) in order to be able to backfill data deleted from publicly available records. In fact, it would be interesting to gain a better understanding of the kind of token offerings that are eliminated from ICO tracking websites *ex post*, and why. A second threat to external validity is that all the information required to conduct the empirical analyses is only available for a subset of all documented token sales. For example, the overlap between transaction data from *ICObench* and pricing data from *coinmarketcap* is less than one third of all token sales, and it is not clear whether token sales present in both samples systematically deviate from those which are present only in one. Again, this is an issue in *all* empirical studies of token sales and implies uncertainty about the generalizability of the results.

Another concern is related to the internal validity of the results. Data comes from entrepreneurial companies themselves or is manually curated by ICO data aggregators, and there is therefore no proven track record or evidence of the accuracy of the data provided. This concern is addressed in two ways. First, information collected from the *ICObench* is validated by comparing the data entries of *ICOalert* and *coingecko*. Second, all hand-collected variables are also manually double-checked. Finally, it is unclear whether the effect of the exaggeration bias in information disclosure will persist in the future. If an efficient market hypothesis is applicable to token offerings (Fama, 1970), the investors' learning about the relationship between exaggeration bias and poor performance in the aftermarket should cause it to cease to exist.

6.5. Avenues for further research

Research on token offerings has only recently begun, and there is therefore a large research agenda with interesting questions on the horizon. In the following, a summary of promising topics not covered in this study is provided.

An unresolved question pertains to the drivers that cause entrepreneurial firms to use token offerings over other financing sources. Similar to crowdfunding (Ahlers et al., 2015), tokens might be issued for promising ideas to reach a global, very large investor base, whereas token sales might also be seen as a 'funding source of last resort' for entrepreneurs who fail to acquire VC. Unlike any other financing source, ventures might also be drawn to token offerings to avoid intermediary fees and/or regulatory scrutiny (Momtaz et al., 2019). Insights into the relative importance of these reasons seem highly relevant.

Also, despite initial studies that explore the determinants of ICO success and related market outcomes (Fisch, 2019; Howell et al., 2018; Momtaz, 2018), very little is known about how social and human capital affects market outcomes such as funding amount, time-to-market, token pricing, liquidity, and the long-run performance of these projects. As Fisch (2019, p. 20) writes, "[f]uture research could explore additional determinants […] such as human and social capital" and especially "founder biographies, education, or professional experience." In a similar vein, very little is known about institutional features such as country- and industry-level factors that might influence token offerings (Huang et al., 2018).

Of great practical relevance are research questions such as what regulatory standards, platform governance, and token exchange policies could promote healthy token market development. Such research might benefit from a better understanding of the heterogeneity of entrepreneurial firms that issue tokens, such as small versus large and young versus relatively old firms, as well as the role of the underlying token type (utility, security, or pure cryptocurrency).

As more and more token issuers use KYC procedures, data at investor level may become available. Investors' identities, preferences, and decision making may greatly inform the knowledge of the dynamics of token offerings; for example, whether investors' revealed preferences vary by time, industry, jurisdiction, and deal structure, and what role distance-related economic frictions play in token offerings (Agrawal et al., 2015). Prior research shows that geographic distance increases the cost of information acquisition and monitoring. For example, Ahlers et al. (2015) find that 53% of investors in equity crowdfunding choose projects that are headquartered in their state of residence. Token-issuing ventures, however, are globally distributed, which makes monitoring challenging and contrasts with investor preferences for geographic proximity in equity crowdfunding. Because it may be difficult to answer all such evolving questions solely based on observable data, qualitative research designs and survey methods may prove useful.

References

Adhami, S., Giudici, G., Martinazzi, S., 2018. Why do businesses go crypto? An empirical analysis of initial coin offerings. J. Econ. Bus. 100, 64–75.
Agrawal, A., Catalini, C., Goldfarb, A., 2015. Crowdfunding: geography, social networks, and the timing of investment decisions. J. Econ. Manag. Strateg. 24, 253–274.
Ahlers, G.K.C., Cumming, D., Günther, C., Schweizer, D., 2015. Signaling in equity crowdfunding. Entrep. Theory Pract. 39, 955–980.
Akerlof, G., 1978. The market for lemons: qualitative uncertainty and the market mechanism. Q. J. Econ. 84, 237–251.
Akerlof, G.A., Kranton, R.E., 2000. Economics and identity. Q. J. Econ. 115, 715–753.
Akerlof, G.A., Kranton, R.E., 2005. Identity and the economics of organizations. J. Econ. Perspect. 19, 9–32.
Amsden, R., Schweizer, D., 2018. Are blockchain crowdsales the new 'gold rush'? Success determinants of initial coin offerings. In: Working Paper. Concordia University.
An, J., Duan, T., Hou, W., Xu, X., 2018. Initial coin offerings and entrepreneurial finance: the role of founders' characteristics. J. Altern. Invest. 21 forthcoming.
Anglin, A.H., Short, J.C., Drover, W., Stevenson, R.M., McKenny, A.F., Allison, T.H., 2018. The power of positivity? The influence of positive psychological capital language on crowdfunding performance. J. Bus. Ventur. 33, 470–493.
Bartov, E., Faurel, L., Mohanram, P.S., 2017. Can Twitter help predict firm-level earnings and stock returns? Account. Rev. 93, 25–57.
Becht, M., Bolton, P., Röell, A., 2003. Corporate governance and control. In: *Handbook of the Economics of Finance*, vol. 1. Elsevier, pp. 1–109.
Benveniste, L.M., Spindt, P.A., 1989. How investment bankers determine the offer price and allocation of new issues. J. Financ. Econ. 24, 343–361.
Bergemann, D., Hege, U., 1998. Venture capital financing, moral hazard, and learning. J. Bank. Financ. 22, 703–735.
Berle, A., Means, G., 1932. *Private Property and the Modern Corporation*.
Bhattacharyya, S., Lafontaine, F., 1995. Double-sided moral hazard and the nature of share contracts. RAND J. Econ. 761–781.
Bianchi, D., 2018. Cryptocurrencies as an asset class? An empirical assessment. In: Working Paper. Warwick Business School.
Blaseg, D., 2018. Dynamics of voluntary disclosure in the unregulated market for initial coin offerings. In: Working Paper. University of Frankfurt.
Boreiko, D., Sahdev, N.K., 2018. To ico or not to ico - empirical analysis of initial coin offerings and token sales. In: Working Paper. Free University Bozano.
Boreiko, D., Vidusso, G., 2018. New blockchain intermediaries: do ICO rating websites do their job well?. In: Working Paper. Free University Bozano.
Busenitz, L.W., Fiet, J.O., Moesel, D.D., 2005. Signaling in venture capitalist–new venture team funding decisions: does it indicate long-term venture outcomes? Entrep. Theory Pract. 29, 1–12.
Chemmanur, T.J., Fulghieri, P., 2013. Entrepreneurial finance and innovation: an introduction and agenda for future research. Rev. Financ. Stud. 27, 1–19.
Chod, J., Lyandres, E., 2018. A theory of ICOs: diversification, agency, and asymmetric information. In: Working Paper. Boston University.
Clayton, J., 2017. Statement on cryptocurrencies and initial coin offerings. In: SEC Press Statement.
Cohen, L., 2008. Loyalty-based portfolio choice. Rev. Financ. Stud. 22, 1213–1245.
Cohney, S., Hoffman, D.A., Sklaroff, J., Wishnick, D.A., 2018. Coin-operated capitalism. In: Working Paper.
Colombo, M.G., Fisch, C., Momtaz, P.P., Vismara, S., 2020. The CEO Beauty Premium. In: Working Paper. UCLA Anderson School of Management.
Connelly, B.L., Certo, S.T., Ireland, R.D., Reutzel, C.R., 2011. Signaling theory: a review and assessment. J. Manag. 37, 39–67.
Davis, B.C., Hmieleski, K.M., Webb, J.W., Coombs, J.E., 2017. Funders' positive affective reactions to entrepreneurs' crowdfunding pitches: the influence of perceived product creativity and entrepreneurial passion. J. Bus. Ventur. 32, 90–106.
Denis, D.J., 2004. Entrepreneurial finance: an overview of the issues and evidence. J. Corp. Finan. 10, 301–326.
Dissanaike, G., Drobetz, W., Momtaz, P.P., Rocholl, J., 2020. Takeover law enforcement and acquirer returns. In: Working Paper. Universities of Hamburg, Cambridge, and UCLA.
Dittmar, R.F., Wu, D.A., 2018. Returns to initial coin offerings: an empirical examination. In: Working Paper. University of Michigan.
Dobrautz, G., Klebeck, U., 2019. Initial coin offerings - legal and regulatory challenges of crossing the border. J. Altern. Invest. 21.
Drobetz, W., Momtaz, P.P., 2019. Corporate governance convergence in the European M&A market. Financ. Res. Lett. https://doi.org/10.1016/j.frl.2019.01.003 in press.
Drobetz, W., Von Meyerinck, F., Oesch, D., Schmid, M., 2018. Industry expert directors. J. Bank. Financ. 92, 195–215.
Drobetz, W., Momtaz, P.P., Schröder, H., 2019. Investor sentiment and initial coin offerings. J. Altern. Invest. 21 (4), 41–55. https://doi.org/10.3905/jai.2019.1.069.
Elitzur, R., Gavious, A., 2003. Contracting, signaling, and moral hazard: a model of entrepreneurs,'angels', and venture capitalists. J. Bus. Ventur. 18, 709–725.
Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Financ. 25, 383–417.
Felix, T., 2018. Underpricing in the cryptocurrency world: evidence from initial coin offerings. In: Working Paper.
Fisch, C., 2019. Initial coin offerings (ICOs) to finance new ventures. J. Bus. Ventur. 34, 1–22.
Fisch, C., Momtaz, P.P., 2020. Institutional Investors and Post-ICO Performance. In: Working Paper. UCLA Anderson School of Management.
Florysiak, D., Schandlbauer, A., 2018. The information content of ico white papers. In: Working Paper.
Fudenberg, D., Tirole, J., 1991. *Game Theory*.
Gompers, P., Lerner, J., 2001. *The Money of Invention: How Venture Capital Creates New Wealth*. Harvard Business Press.
Gompers, P.A., Lerner, J., 2004. *The Venture Capital Cycle*. MIT press.
Gompers, P., Ishii, J., Metrick, A., 2003. Corporate governance and equity prices. Q. J. Econ. 118, 107–156.
Heckman, J., 1979. Sample selection bias as measurement error. Econometrica 47, 153–161. January.
Hellmann, T., Puri, M., 2002. Venture capital and the professionalization of start-up firms: empirical evidence. J. Financ. 57, 169–197.
Hölmstrom, B., 1979. Moral hazard and observability. Bell J. Econ. 74–91.
Houben, E., 2002. Venture capital, double-sided adverse selection, and double-sided moral hazard. In: Working Paper. Kiel University.
Howell, S.T., Niessner, M., Yermack, D., 2018. Initial coin offerings: financing growth with cryptocurrency token sales. In: Working Paper. National Bureau of Economic Research.
Hu, M., Liu, B., 2004. Mining Opinion Features in Customer Reviews, 4, pp. 755–760.
Huang, W., Meoli, M., Vismara, S., 2018. The geography of initial coin offerings. In: Working Paper. University of Ghent.
Hurt, C., 2004. Moral hazard and the initial public offering. Cardozo L. Rev. 26, 711.
Iansiti, M., Lakhani, K.R., 2017. The truth about blockchain. Harv. Bus. Rev. 95, 118–127.
Jensen, M.C., Meckling, W.H., 1976. Theory of the firm: managerial behavior, agency costs and ownership structure. J. Financ. Econ. 3, 305–360.
Kaal, W., Dell'Erba, M., 2017. Initial coin offerings: emerging practices, risk factors, and red flags. In: Working Paper.
Kastelein, R., 2017. What initial coin offerings are, and why VC firms care. Harv. Bus. Rev. 24.

Kean, B., 2018. Don't believe the hype. Five largest ico "exit scams. In: Technical report. https://cointelegraph.com/news/dont-believe-the-hype-the-fivelargest-ico-exit-scams-expert-take.
Khurshed, A., 2011. *Initial Public Offerings: The Mechanics and Performance of IPOs*. Harriman House Limited.
Kostovetsky, L., Benedetti, H., 2018. Digital tulips? Returns to investors in initial coin offerings. In: Working Paper. Boston College.
Kremer, I., Mansour, Y., Perry, M., 2014. Implementing the "wisdom of the crowd". J. Polit. Econ. 122, 988–1012.
Lee, W.Y., Jiang, C.X., Indro, D.C., 2002. Stock market volatility, excess returns, and the role of investor sentiment. J. Bank. Financ. 26, 2277–2299.
Leitterstorf, M.P., Rau, S.B., 2014. Socioemotional wealth and IPO underpricing of family firms. Strateg. Manag. J. 35, 751–760.
Leland, H.E., Pyle, D.H., 1977. Informational asymmetries, financial structure, and financial intermediation. J. Financ. 32, 371–387.
Li, J., 2016. Profit-sharing, wisdom of the crowd, and theory of the firm. In: Working Paper. George Mason University.
Li, J., Mann, W., 2018. Initial coin offering and platform building. In: Working Paper. UCLA.
Li, X., Masulis, R.W., 2004. Venture capital investments by IPO underwriters: certification, alignment of interest or moral hazard?. In: Working Paper.
Lipausch, N., 2018. Initial coin offerings - a paradigm shift in funding disruptive innovation. In: Working Paper. University of Kassel.
Liu, Y., Tsyvinski, A., 2018. Risks and returns of cryptocurrency. In: Working Paper. National Bureau of Economic Research.
Ljungqvist, A., 2007. IPO underpricing. In: *Handbook of corporate finance: Empirical corporate finance*, 1, pp. 375–422.
Ljungqvist, A., Wilhelm Jr, W.J., 2003. Ipo pricing in the dot-com bubble. J. Financ. 58, 723–752.
Lyandres, E., Palazzo, B., Rabetti, D., 2018. Are tokens securities? An anatomy of initial coin offerings. In: Working Paper.
MacKinlay, A.C., 1997. Event studies in economics and finance. J. Econ. Lit. 35, 13–39.
Malinova, K., Park, A., 2018. Tokenomics: when tokens beat equity. In: Working Paper. McGill University.
Michaely, R., Womack, K.L., 1999. Conflict of interest and the credibility of underwriter analyst recommendations. Rev. Financ. Stud. 12, 653–686.
Mirrlees, J.A., 1999. The theory of moral hazard and unobservable behaviour: part i. Rev. Econ. Stud. 66, 3–21.
Mollick, E., 2014. The dynamics of crowdfunding: an exploratory study. J. Bus. Ventur. 29, 1–16.
Momtaz, P.P., 2018. Initial coin offerings. In: Working Paper. UCLA Anderson.
Momtaz, P.P., 2019a. CEO emotions and firm valuation in initial coin offerings: an artificial emotional intelligence approach. In: Working Paper. UCLA Anderson.
Momtaz, P.P., 2019b. Token sales and initial coin offerings: introduction. J. Altern. Invest. 21 (4), 7–12. https://doi.org/10.3905/jai.2019.21.4.007.
Momtaz, P.P., 2020a. Initial coin offerings, asymmetric information, and CEO loyalty. Small Bus. Econ. in press.
Momtaz, P.P., 2020b. The pricing and performance of cryptocurrency. Eur. J. Financ. https://doi.org/10.1080/1351847X.2019.1647259 in press.
Momtaz, P.P., 2020c. Time-to-event models. In: Working Paper. UCLA Anderson School of Management.
Momtaz, P.P., Rennertseder, K., Schroeder, H., 2019. Token offerings: a revolution in corporate finance? J. Financ. Transform. 49, 32–42.
Moss, T.W., Renko, M., Block, E., Meyskens, M., 2018. Funding the story of hybrid ventures: crowdfunder lending preferences and linguistic hybridity. J. Bus. Ventur. 33, 643–659.
Nakamoto, S., 2008. Bitcoin: a peer-to-peer electronic cash system. In: Technical report.
Natarajan, H., Krause, S., Gradstein, H., 2017. Distributed Ledger Technology and Blockchain.
Officer, M.S., 2007. The price of corporate liquidity: acquisition discounts for unlisted targets. J. Financ. Econ. 83, 571–598.
Porta, R.L., Lopez-de Silanes, F., Shleifer, A., Vishny, R.W., 1998. Law and finance. J. Polit. Econ. 106, 1113–1155.
Rhue, L., 2018. Trust is all you need: an empirical exploration of initial coin offerings (ICOs) and ICO reputation scores. In: Working Paper.
Ritter, J.R., Welch, I., 2002. A review of IPO activity, pricing, and allocations. J. Financ. 57, 1795–1828.
Rogerson, W.P., 1985. Repeated moral hazard. Econometrica 69–76.
Shifflett, S., Jones, C., 2018. Buyer Beware: Hundreds of Bitcoin Wannabes Show Hallmarks of Fraud.
Spence, M., 1973. Job Market Signaling, 87, pp. 355–374.
Syer, M.D., Nagappan, M., Adams, B., Hassan, A.E., 2015. Studying the relationship between source code quality and mobile platform dependence. Softw. Qual. J. 23, 485–508.
Tirole, J., 2001. Corporate governance. Econometrica 69, 1–35.
Tirole, J., 2010. *The Theory of Corporate Finance*. Princeton University Press.
Vismara, S., 2016. Equity retention and social network theory in equity crowdfunding. Small Bus. Econ. 46, 579–590.
Vismara, S., 2018. Signaling to overcome inefficiencies in crowdfunding markets. In: *The Economics of Crowdfunding*. Springer, pp. 29–56.
Yermack, D., 2017. Corporate governance and blockchains. Review of Finance 21, 7–31.
Zetzsche, D.A., Buckley, R.P., Arner, D.W., Föhr, L., 2018. The ICO gold rush: it's a scam, it's a bubble, it's a super challenge for regulators. In: Working Paper. Luxembourg Law School.