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The Financial and Non-Financial Performance of Token Offerings

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The Financial and Non-Financial Performance of Token-Based Crowdfunding: Certification Arbitrage, Investor Choice, and the Optimal Timing of ICOs

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Abstract

What role does the selection of an investor and the timing of financing play in initial coin offerings (ICOs)? We investigate the operating and financial performance of ventures conducting ICOs with different types of investors at different points in the ventures' life cycle. We find that, relative to purely crowdfunded ICO ventures, institutional investor-backed ICO ventures exhibit poorer operating performance and fail earlier. However, conditional on their survival, these ventures financially outperform those that do not receive institutional investor support. The diverging effects of investor backing on financial and operating performance are consistent with our theory of certification arbitrage; i.e., institutional investors use their reputation to drive up valuations and quickly exit the venture post-ICO. Our findings further indicate that there is an inverted U-shaped relationship for fundraising success of ICO ventures over their life cycle. Another inverted U-shaped relationship exists for the short-term financial performance of ICO ventures over their life cycle. Both the fundraising success and the financial performance of an ICO venture initially increase over the life cycle and eventually decrease after the product piloting stage.

Keywords: Token Offering, Initial Coin Offering (ICO), Crypto Funds, Operating versus Financial Performance, Entrepreneurial Finance, Optimal Timing
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1 Introduction

Entrepreneurial financial markets are very competitive, especially on the demand side for capital. Many entrepreneurs are desperate for funding "just to keep going" and miss the opportunity to focus their fundraising efforts on getting the best partners on board on setting the course for long-term success. Thus, there is a highly *strategic* aspect to early-stage entrepreneurial finance (Amornsiripanitch et al., 2019; Blaseg and Hornuf, 2023; Mansouri and Momtaz, 2022). Strategic entrepreneurial finance of pre-seed and seed ventures nevertheless remains a largely underexplored research field, with numerous challenges for establishing empirical facts to inform theory, including segmentation of early-stage financing markets, which precludes an empirical analysis of optimal financing choices and strategies (Cumming and Johan, 2017). In this study, we explore two overarching strategic aspects of entrepreneurial finance in the context of blockchain technology-based ventures that tokenize their assets and sell them through initial coin offerings (ICOs). First, we study whether there are differences in crowdfunded versus institutional investor-backed ventures in terms of their post-funding operating and financial performance. Second, we investigate whether there is an optimal point in time along a startup's life cycle to raise capital through token offerings.

Token offerings present a near-ideal laboratory for exploring these questions empirically for two key reasons. First, token markets are relatively *integrated* with regard to participating investor types. Although the ICO market is often thought of as a sophisticated form of crowdfunding (Fisch, 2019), many institutional investors, often referred to as *crypto funds*, co-invest alongside individuals in ICOs (Fisch and Momtaz, 2020). Even among crypto funds, there is variation with regard to their investment strategy. Some crypto funds are geared toward the potential operating performance of the target company and thus resemble traditional venture capitalists (*crypto venture funds*), while others are more interested in the financial performance of the target company and resemble traditional hedge funds (*crypto hedge funds*) (Cumming et al., 2022; Dombrowski et al., 2023). This heterogeneity in investor type can be empirically exploited to study the question of optimal investor choice. Second, markets for tokens are relatively integrated in terms of the startup life cycle stage of the entrepreneurial ventures seeking financing. ICOs nevertheless vary in size, ranging from micro-cap ($0.1 million or less) to mega-cap (several billions) funding rounds (Bellavitis et al., 2020; Bellavitis et al., 2021; Momtaz, 2020). ICO ventures also differ, at least in part, in their life cycle stages during the ICO, which we conceptualize as ranging from ideation to profitability. The inclusiveness of the ICO market therefore provides a great deal of heterogeneity to be exploited in addressing the question of optimal timing for tapping entrepreneurial finance markets.

The empirical context of token offerings also offers interesting ground for novel theorizing. Entrepreneurial finance is inherently risky because it involves a high level of information asymmetry between ventures seeking funding and the investors providing the capital (e.g., Cumming, 2008; Cumming and Johan, 2017; Drover et al., 2017; Dushnitsky and Shapira, 2010). Theory suggests that ventures may reduce such asymmetries by sending costly signals of venture quality (Ahlers et al., 2015; O. Colombo, 2021; Vismara, 2018). However, in the era of tokenization of future assets, traditional signals have become increasingly ineffective (Bourveau et al., 2022; Fisch, 2019) chiefly due to a lack of institutional framework that would verify signals *ex ante* or, at the very least, punish false signals *ex post* (Momtaz, 2021c). Many tokenized startups are thus returning to outside certification (as opposed to an endogenous signal) by enlisting the support of institutional investors (M. Colombo et al., 2021; Fisch and Momtaz, 2020).

We depart from the prevalent view of uniformly beneficial certification through institutional investors (e.g., Fisch and Momtaz, 2020; Hsu, 2004) and argue that institutional investor backing can have heterogeneous consequences for the performance of tokenized ventures. The rationale for different forms of certification builds on a novel form of professional pump-and-dump schemes in entrepreneurial finance, which we call *certification arbitrage*. In the context of tokenized ventures, certification arbitrage occurs when institutional investors, who attest to the quality of the venture with their financial backing, have an incentive to quickly exit a target venture as long as token valuations are favorably impacted by their certification. Put differently, certifying investors buy tokens at the pre-certification price and, thanks to liquid secondary markets, sell their tokens almost immediately at the post-certification price, with the difference being their arbitrage profit.

The possibility of certification arbitrage can lead to individually rational market myopia (Stein, 1989). If entrepreneurs know about the certifying investors' exit incentive, they may focus on activities that boost short-term financial performance (i.e., increasing the token price) to keep investors aboard and hence forego activities that would benefit long-term operating performance. As a consequence, certification arbitrage leads to diverging effects on startups' operating versus financial performance. Accordingly, our *Operating Underperformance Hypothesis* and our *Financial*

Outperformance Hypothesis posit that, *ceteris paribus,* institutional investor-backed ICO ventures have poorer operating performance and stronger financial performance, respectively, than solely crowdfunded ICO ventures.

We also develop theoretical arguments pertaining to the optimal timing to conduct a token offering. At least three arguments suggest that conducting ICOs very early and very late along a startup's life cycle may dampen the offering's success and financial performance of a token offering. First, token offerings involve a trade-off between entrepreneurs giving up private benefits of control as well as gaining from cashing out versus increasing the venture's value (Benninga et al., 2005). Private benefits accrue as ventures mature, while the marginally increased value-add of institutional investors decreases as ventures mature because information asymmetries decrease. Second, learning from market feedback in token offerings may be overwhelming for pre-seed ventures and of little marginal use for very mature ventures (Yan and Williams, 2021). Third, the potential benefits of certification in early-stage and mature ventures are small because certification may not be credible in early stages and may not be profitable later on. Together, these arguments lead to our *Optimal Timing Hypothesis* (OTH), which posits that there are two inverted U-shaped relationships. A first inverted U-shaped relationship exists between the fundraising success of ICO ventures and their life cycle. The other inverted U-shaped relationship is between the short-term financial performance of ICO ventures and their life cycle.

We test our hypotheses using a sample and database that tracks the operating performance of tokenized startups over the period 2015–2021 in terms of their achieved and missed milestones. Our classification of milestones considers seven phases spanning idea, proof of concept, prototype, pilot, minimum viable product, full product, and operational success or profitability. Overall, our data set tracks 20,431 milestones in 3,864 startups. This novel database on actual operating performance of startups enables documentation of several stylized facts. First, of all ventures, only about half ultimately develop a full product and only 19% reach the stage of operational success. Second, conditional on achieving this milestone, startups that develop a full product take about 19 months and startups that are operationally successful take about 24 months from ideation to reach this stage. Third, the most common reasons why startups fail are that they are not able to develop their pilot into a minimum viable product or their minimum viable product into a full product. More than 60% of all startups fail during the stages from pilot to full product development, which occupy a relatively short time span of three months for the average startup in our sample.

As in most entrepreneurial finance research, it is non-trivial to empirically test our three hypotheses due to endogeneity concerns. The endogeneity concerns stem from the fact that startups often adhere to latent unobserved heterogeneity, and outcomes could be affected by these unobserved factors. Accounting for unobserved heterogeneity is therefore essential and not doing so can lead to biases in time-to-event estimates. Frailty models, which were introduced by Vaupel et al. (1979), minimize these biases, especially when compared to Cox Proportional Hazards models (Momtaz, 2021b). Estimating frailty models, our empirical results provide evidence supporting our hypotheses.

First, compared to crowdfunded startups, institutional investor-backed startups have a lower likelihood of survival. The frailty models reveal that institutional investor-backed startups fail before they are profitable or have developed a full product, with increased hazards of 24 and 42%, respectively, supporting our Operating Underperformance Hypothesis. We also show that the effect is primarily driven by crypto hedge funds, not by crypto venture funds. Additionally, we explore the relation between the funding amount and the time-to-liquidation. Because the funding amount could be endogenously determined by the *unobserved* propensity of a startup to become operationally successful, we employ a two-stage least squares approach, which suggests that funding significantly prolongs startups' efforts to develop a full product or become profitable.

Second, relative to crowdfunded startups, we also find that institutional investor-backed startups are able to raise more financing, and their financial performance in terms of buy-and-hold abnormal token returns is higher in the short term (up to six months) and non-significantly different in the longer term (24 months), partially supporting our Financial Outperformance Hypothesis. Importantly, these results hold conditional on startups' operating performance, suggesting that financial performance for the average startup in our sample declines over time. As before, we explore whether the type of institutional crypto hedge funds and crypto venture funds negatively affect ventures' financial performance; however, the impact of the former is substantially larger.

Third, we follow Haans et al. (2016) in testing the inverted U-shaped relationships between the success of the offering as well as financial performance and their timing along the startup life cycle. The results are highly consistent irrespective of whether startups want to optimize the timing of their token offering with an eye toward maximizing the funding amount or the short-term financial returns to investors. For entrepreneurs wishing to maximize the funding amount, the optimal timing to conduct a token offering is right upon the completion of the piloting milestone, when startups begin to develop the minimum viable product. Similarly, for entrepreneurs wishing to maximize short-term investor returns, the optimal timing to conduct a token offering is during the piloting milestone. However, we do not find that long-term financial performance of tokenized startups can be influenced by the timing of the offering. In sample-split analyses, we explore whether the optimal timing of token offerings hinges on whether it is a purely crowdfunded or institutional investor-backed project. We find that timing is particularly important for short-term financial returns in ventures with institutional investor backing.

The remainder of this article is organized as follows. Section 2 provides institutional background and develops our empirical predictions. Section 3 describes our data and empirical method. Section 4 presents the results, and Section 5 concludes.

2 Background and Hypotheses

2.1 Institutional background

2.1.1 Token-based crowdfunding and the aftermarket for tokenized startups

In a token offering, or ICO, startups raise capital by selling tokens to investors (Fisch, 2019; Momtaz, 2020).[1] Tokens are cryptographically protected digital units of assets that provide value to investors through a utility, currency, or security function (Howell et al., 2020; Ofir and Sadeh, 2021). Utility tokens are voucher-like assets, which give access to a service or product the issuing venture promises to provide in the future, and are the most frequently issued token type in ICOs (Bellavitis et al., 2020; Momtaz, 2020).[2] ICOs represent an innovative entrepreneurial finance mechanism that has evolved from crowdfunding by way of blockchain technology to issue stakes in startups (Belitski and Boreiko, 2021; Fisch, 2019; Howell et al., 2020; Huang et al., 2020; Li

[1] Unlike other entrepreneurial financing mechanisms, ICOs integrate the full spectrum of funding volumes (Momtaz, 2022a), ranging from micro-cap ICOs (<$100,000) to mega-cap ICOs (>$1,000,000, such as the EOS campaign in 2018, with more than $4 billion raised).

[2] In contrast to digital currencies, which serve as a means of payment that is external to the token platform, utility tokens grant rights to a certain platform where the issuer's service is provided. Unlike security tokens, utility tokens do not grant ownership rights. Recent developments in ICO regulation have, *inter alia*, initiated a gradual shift from utility to security token offerings (Lambert et al., 2021).

and Mann, 2018; Momtaz, 2020). ICOs also share common features with venture capital and initial public offerings (Chod and Lyandres, 2021; Malinova and Park, 2018; Ofir and Sadeh, 2021). Technically speaking, ICOs are decentralized startup financing transactions that rely on smart contracts to automate "trustless" transactions between entrepreneurs and investors (Amsden and Schweizer, 2018; Fisch et al., 2022; Momtaz, 2022a).[3]

From an issuing firm's perspective, utility token offerings have several benefits. First, startups can raise capital from investors without diluting their equity holdings in utility-token ICOs. Second, the ICO mechanism facilitates access to a global investor base at very low transaction costs. Third, issuers are able to cultivate new users for their products or services, who will be particularly likely to engage with the project. Fourth, investors join the platform not only to enjoy its utility, but also to benefit from the rising token price as a result of growing network size (Benedetti and Nikbakht, 2021; Cong et al., 2021; Howell et al., 2020; Ofir and Sadeh, 2021).

From an investor's perspective, tokenized startups have several distinct benefits, mostly related to aftermarket potential. Tokens are *fungible* and *fractionalizable*, which means that investors can trade them on public and liquid secondary markets at arbitrarily low prices per fractionalized unit. Tokens can be either exchanged among investors or converted into other cryptocurrencies or fiat currencies on liquid cryptocurrency exchanges. This ease of trading makes investing in ICOs easier and less costly compared to IPOs, as there is no need to use the services of a broker. And because token investors can exit their portfolio ventures anytime, they—unlike venture capitalists—have a lower burden of "backing the next unicorn" to make up for failed investments. Tokens also attract more individual investors to early-stage startup financing markets who would otherwise stay away if they had to commit to the investment for several years before seeing a potential return, thus democratizing access to finance (Y. Chen and Bellavitis, 2020; Fisch et al., 2022). Evidence from stock markets suggests that public markets also entail economic costs, which might be particularly salient if early-stage ventures are traded. There are obvious costs for investor relations and regulation in public markets (Bellavitis et al., 2021; Mokhtarian and Lindgren, 2018). There are also less obvious costs, such as market myopia, which we discuss below, because they might be a particular problem in the market for tokenized ventures.

[3] Brochado and Troilo (2021) and Ofir and Sadeh (2021) survey the rapidly evolving ICO literature.

2.1.2 Crypto funds

Token offerings can be either wholly crowdfunded by individual investors or obtain additional institutional investor backing (Fisch and Momtaz, 2020). Institutional investors in tokenized startups are referred to as *crypto funds*, and typically employ either of two common investment strategies (Cumming et al., 2022). Just like traditional venture capital funds (e.g., M. Colombo and Grilli, 2010), crypto venture funds can be business model-oriented investors that support a venture, for example, by setting up the blockchain and helping scale the technology. They often perform other functions, such as providing guidance and coaching (for example, through control or voting rights as part of their governance token ownership) in the startup's management and/or technology team. However, unlike other investors in startups, many crypto funds are purely financially oriented and employ a hedge fund-style investment strategy (Cumming et al., 2022; Dombrowski et al., 2023; Momtaz, 2022a). Because tokenized startups can be traded anytime on liquid token exchange platforms (e.g., Momtaz, 2021c), some crypto hedge funds employ sophisticated trading strategies, including short selling of tokens, to take advantage of arbitrage opportunities. These purely financially motivated crypto hedge funds do not necessarily consider what is best for their portfolio startups in the long run. In fact, their behavior can lead to detrimental outcomes for the firms, which we discuss further below. Hedge fund-style trading of startups is novel and only became possible through the tokenization of ventures and the creation of public markets for tokens (Dombrowski et al.).

2.2 Theoretical background and hypotheses

2.2.1 Investor choice in entrepreneurial finance

Whether founders choose investors strategically and what type of investors they choose can have a significant impact on a venture's subsequent operational and financial performance. In addition to fund manager talent, the geographic and funding-phase specialization of venture capital funds has a theoretically and empirically positive effect on the performance of portfolio companies (Han, 2009). A venture capital fund specializing in early-stage financing is often less efficient than general institutional investors when it comes to supporting the operational performance of companies beyond the pre-seed and seed stage round (Schwienbacher, 2013), which could make crypto venture funds a better choice for founders when operational performance is the goal. In reality, however, founders often choose venture capitalists who are more likely to help expand the operational network and accompany the exit than to provide strategic advice and help with internal company development as coaches (Granz et al., 2021). Therefore, financial performance of the venture might also have particular appeal for founders. Moreover, not all founders choose their investors strategically. Drover et al. (2014) show that as a venture's need for capital increases, founders become increasingly accepting of unethical venture capital funds. Translated into tokenized venture financing, the demand for capital could drive the acceptance of crypto funds, which are more likely to engage in certification arbitrage.

Little is known about the strategic entrepreneurial choice of investors for tokenized ventures. Coakley et al. (2021) have studied the strategic choice for founders between competing crowdfunding platforms and find that a large and more heterogeneous founder team is more likely to choose a crowdfunding platform that allows the crowd to co-invest with institutional investors. This is because larger founding teams are inherently better at sending quality signals, a capability that is enhanced through the presence of an institutional investor (Ralcheva and Roosenboom, 2016. On the other hand, larger founder teams are less likely to choose a nominee ownership structure, because they are better able to deal with the post-campaign administrative burden themselves.

2.2.2 Crypto funds and tokenized startups' operating vs. financial performance

Crypto funds re-centralize decentralized finance to some degree by pooling individual investors' funds (Cumming et al., 2022; Zetzsche et al., 2020). A reason for the growing importance of crypto funds in tokenized markets for entrepreneurial finance is their ability to produce information more efficiently than crowd investors (Fisch and Momtaz, 2020). By pooling individual investors' funds, they are able to exploit economies of scale in information production, which is particularly relevant in entrepreneurial finance because such markets typically feature salient information asymmetries between entrepreneurs and investors. Asymmetric information is a pervasive problem because investors seeking to back early-stage entrepreneurs cannot rely on existing assets as collateral or on existing track records, which are often too short—if they exist at all—to serve as indicators of potential success trajectories (M. Colombo and Grilli, 2010; O. Colombo, 2021; Jensen et al., 1976). The asymmetric information problem is particularly pronounced in the context of tokens because, first, entrepreneurs tokenize future assets often long before they are even produced and, second, there is substantial uncertainty about the prospects of the blockchain industry overall. If unaddressed, asymmetric information can cause market failure (Akerlof, 1978). If investors cannot discern the quality of a token, equilibrium pricing of the token will settle on the population average, which would crowd out high-quality tokens and crowd in low-quality tokens, ultimately resulting in a race to the bottom of venture quality. Therefore, to prevent market failure, entrepreneurs and investors in entrepreneurial finance markets typically put effort into creating mechanisms that reduce information asymmetries.

Theory suggests that entrepreneurs may reduce information asymmetries by sending signals of venture quality (O. Colombo, 2021). Signals must be costly to be credible and they must be observable to have an effect in markets (Connelly et al., 2011). The seminal article in entrepreneurial finance by Leland and Pyle (1977) argues that high-quality ventures will retain an equity share, while low-quality ventures will sell all equity when possible. The result is a separating equilibrium, which may resolve the problem of asymmetric information in startup equity financing. The concept has been applied to venture capital (Busenitz et al., 2005), equity crowdfunding (Ahlers et al., 2015; Vismara, 2016), and token offerings (Davydiuk et al., 2023; Fisch, 2019). However, the applicability of signaling is controversial in token offerings, *inter alia*, because most signals in token offerings are not costly but rather considered "cheap talk" (Bourveau et al., 2022) and, in the absence of regulation, often are exaggerated and not enforceable (Momtaz, 2021c). Consequently, empirical work has shown that many traditional signals do not work in the context of token offerings (Fisch, 2019).

When there are limitations to signaling, asymmetric information problems can be mitigated if trustworthy and informed third parties certify the venture's quality to the market (Hsu, 2004). Typically, institutional investor backing is associated with a certification mechanism because institutional investors often have the resources and skills to determine a venture's true quality, and if due diligence leads to an institutional investment, then uninformed market participants often follow (Hornuf and Schwienbacher, 2018). Not only does this dominant view assume that institutional investors do not use their market power as certifying authorities to impact markets in their favor, but it also neglects the fact that certification *per se* increases a venture's market value in the short run. In traditional entrepreneurial finance markets, where institutional investors are locked into their investments for years due to the illiquidity of markets for startups, certification theory may in essence be useful. We argue, however, that it is necessary to depart from the classical certification paradigm in the context of tokenized startups that can be traded in liquid markets, because institutional investors can now quickly dump their investments after their certification has paid off. Departing from the classical assumptions in the dominant view may dramatically change market predictions of the certifier's impact on ventures.

The core of our modified certification theory is that, in the context of tokens, certifiers are well aware of their certification's market impact on the venture's value and of their certifications' market power to manipulate prices, which they may exploit to extract private benefits. These conditions lend themselves to a novel moral hazard in entrepreneurial finance, which we refer to as *certification arbitrage*. By implication, the possibility of certification arbitrage plausibly exacerbates market myopia. Myopia refers to the phenomenon that some "managers tend to make decisions that yield short-term gains at the expense of the long-term interests of the shareholders" (Narayanan, 1985, p. 1469). The theory of market myopia submits that long-term, uncertain projects are difficult to communicate and therefore are not fully reflected in the stock price, which is why myopic managers forego those projects; that is, they avoid projects that are good for operating efficiency in the long term and focus instead on projects that are good for stock price in the short term (Stein, 1989). The presence of institutional investors can exacerbate myopia. For example, hedge funds rarely think beyond a 20-month investment horizon (Brav et al., 2008). To generate a quick return, hedge funds often require that target companies cut their costs (Gillan and Starks, 2009; Westphal and Bednar, 2008), reduce investments (Bebchuk et al., 2015), and reallocate assets to free up funds to pay dividends to investors (Brav et al., 2015; S. Chen and Feldman, 2018).

Crypto funds and the possibility of certification arbitrage amplify the myopia problem for tokenized startups for at least two reasons. First, crypto funds trade mostly in tokens that are legally classified as utility tokens or "non-securities" (Mokhtarian and Lindgren, 2018), which exempts crypto funds (unlike any other institutional investors in entrepreneurial finance markets) from regulations that would prevent market misconduct such as certification arbitrage. Second, with the possibility of certification arbitrage, crypto funds have an even stronger incentive to exit because the arbitrage profit decreases over the course of the investment period, thus increasing pressure on the crypto funds to exit and on the entrepreneur to increase the token price. Because entrepreneurs know about the certifying investors' exit incentive, it is rational for them to focus on activities that boost short-term financial (i.e., token price) performance and forego activities that would benefit long-term non-financial (i.e., operating) performance.

Hypothesis 1 *Crypto fund backing is associated with a negative effect on the operational survival of tokenized startups. (Operating Underperformance Hypothesis)*

Hypothesis 2 *Conditional on operational survival, crypto fund backing is associated with a positive effect on the financial success of tokenized startups. (Financial Outperformance Hypothesis)*

As with many predictions in entrepreneurship and entrepreneurial finance, the predicted effects might be heterogeneous (Newbert et al., 2022). These first two hypotheses in particular are contingent on different types of crypto funds. Crypto funds are usually either quantitative investors (crypto hedge funds) or more business model-oriented (crypto venture funds). The aforementioned evidence (i.e., Bebchuk et al., 2015; Brav et al., 2008) would predict that the hypothesized effects are more pronounced for crypto hedge funds. In contrast, venture capital-style funds often have longer-term investment horizons and provide non-financial services, such as board advice or access to their network (Cumming, 2008; Cumming et al., 2005; Cumming and Johan, 2013; S. N. Kaplan and Stromberg, 2001; Metrick and Yasuda, 2021). Therefore, while we do not develop these arguments into formal hypotheses, we would expect that crypto hedge funds' positive effect on financial performance and negative effect on operating performance are more pronounced than those of crypto venture funds. We test and discuss these additional predictions in the results section.

2.2.3 Optimal timing for token offerings along startups' life cycle

The timing of raising venture finance on public markets substantially impacts the success of the fundraising campaign. Many studies examine "market timing," i.e., how external factors such as the macroeconomy affect the timing of ventures' financing decisions (e.g., Bellavitis et al., 2022; Opp, 2019). In addition to market timing, the timing of the investment during the life cycle of a startup also plays a role. Gompers (1995) shows that venture capitalists typically concentrate their investments in the early stages of ventures and high-technology projects where information asymmetries are highest. This is because early-stage venture capitalists are often specialized in seed financing and are therefore more efficient in assisting a venture during the early-stage rounds than other professional investors (Schwienbacher, 2013). However, the optimal timing with regard to startups' current development stage along the startup life cycle from ideation to profitability is still relatively underexplored (Yan and Williams, 2021). The optimal timing to raise external venture financing on public markets along ventures' life cycle is essentially a function of, first, the advantages and disadvantages of pivoting from being a private to being a public firm (Benninga et al., 2005) and, second, the costs and benefits of conducting the token offering *per se*.

According to Benninga et al. (2005), pivoting from private to public company status involves a trade-off between giving up private benefits of control on the one hand and cashing out and benefiting from the company's increased firm value as a public company on the other hand. An entrepreneur's private benefits of control include the status and prestige of being an entrepreneur, enjoying the lower regulatory burden of a private company, and behavior and decisions that incur agency costs to the firm, among others. Pivoting to public company status does have value-increasing benefits, including external scrutiny in the form of management monitoring, funding for new investments, marketability of shares in the venture, and information in the form of market prices to infer the venture's equilibrium value. There are nevertheless costs associated with being public, including transaction costs such as advisory fees, maintenance costs such as resources for investor relations, and strategic costs in the form of information disclosure to competitors.

From a capabilities perspective, there is a trade-off between the learning advantages of newness and the liability of newness when new ventures enter new markets, such as the market for tokens. For example, Yan and Williams (2021) report an inverted U-shaped relationship between the venture's age at the time of its international entry and its growth trajectory. The learning advantages of newness stem from the fact that far-reaching decisions, such as conducting a token offering, expose the venture team to substantial uncertainty (M. Colombo et al., 2021; Fisch, 2019; Momtaz, 2021a, 2022b), which in turn requires them to develop new routines, rules, and capabilities more broadly. Therefore, when token offerings lead to improved capabilities in the new venture team, the value of the venture potentially increases. In contrast, the liability of newness comes from a lack of existing roles, rules, and capabilities, as well as a lack of legitimacy with stakeholders and resources. Conducting a token offering also has substantial opportunity costs because doing so requires significant attentional and financial investments (Momtaz, 2020) and leads to a limbo period between a successful offering and the establishment of a liquid market for the exchange of the venture's tokens, a period during which 70–80% of all ICO ventures fail (Cumming et al., 2022; Momtaz, 2021c). Hence, for startups during the pre-seed and seed phases, token offerings may require prohibitively costly investments, whereas at relative maturity, there may be hardly any benefits to conducting a token offering.

From an asymmetric information perspective, there is a trade-off in the value of outside certification. Pre-seed and seed startups are characterized by a relatively high degree of asymmetric information. In this case, institutional investors cannot certify venture quality in a credible way given their non-existent track record and lack of a mature business idea. Thus, pre-seed and seed ventures have little to gain from conducting a token offering too early. In contrast, growth-phase startups are characterized by a relatively low degree of asymmetric information. In this case, the market may possess sufficient information about the venture's prospects, such as market size, revenue and profit margins, and human capital. Therefore, arbitrage profit for certifying institutional investors is limited. It would also require a credible explanation on the part of the startup as to why additional capital from institutional investors is needed when the startup is already profitable.

Hypothesis 3 *There is an inverted U-shaped relationship between the financial success of the offering and its timing over the life cycle of the venture. (**Optimal Timing Hypothesis**)*

Hypothesis 4 *There is an inverted U-shaped relationship between the financial performance of the token offering and its timing over the life cycle of the venture. (**Optimal Timing Hypothesis**)*

3 Data and Stylized Facts

3.1 Data sources and sample construction

To assess the operational and financial performance of tokenized startups, we build upon the *Token Offerings Research Database* (*TORD*),[4] which was initially created in connection with the re-

[4]Available at www.paulmomtaz.com/data/tord.

search project of Cumming et al. (2022) and represents one of the largest and most comprehensive databases on token-based crowdfunding (i.e., ICOs) (Momtaz, 2022c). It aggregates data from various sources, including *ICObench*, *ICOmarks*, *GitHub*, and *LinkedIn*, among others, and encompasses more than 6,000 startups.

From the work of Cumming et al. (2022), we adopt the manual mapping of the *TORD* to token performance as well as crypto fund (CF) data. Token performance data is the secondary market based on *CoinMarketCap* and includes prices, market capitalizations, and trading volumes until October 2020. We leverage this data to measure the financial performance of startups in the aftermarket via their tokens' abnormal returns compared to a value-weighted market index. CF data comes from *Crypto Fund Research* and is used to derive which startups received CF backing and the funds' respective investment strategy (crypto venture fund vs. crypto hedge fund). This data enables us to determine the financial and operational impact of CF backing as well as any effect difference in the investment strategy.

In order to measure the startups' operational performance, we expand the *TORD* using a set of operational indicators. For this, we draw upon self-reported milestone data from *ICObench* and manually cluster them into milestone steps along a typical startup life cycle. This begins with identifying common reporting themes, which allows us to determine reoccurring phrases that are used to group the milestones into specific project achievements. These classifications are then manually checked and refined. As a last step, we cluster all project achievements into seven milestone steps: idea, proof of concept (PoC), prototype, pilot, minimum viable product (MVP), full product, and operational success.

The milestone *idea* represents the first step at the start of the venture. Often, this is characterized by the announcement of the startup's founding or the initial communication regarding its idea, concept, or the road map it plans to pursue. The *PoC* step indicates that the startup has successfully validated its concept. The subsequent development of a prototype or demo version of the product/service is captured by our category *prototype*. During the *pilot* phase, this prototype is experimented with, e.g., in a simulated software environment or via a trial version for a selected number of test users. Following successful piloting, an *MVP* is developed and initially launched with limited functionality and/or for a limited audience (e.g., a specific geographical region or operating system). Based on the experiences of the MVP, the *full product* milestone is defined as the first full version of the product/service that is released to a broader market. Usually, this launch takes place across various operating systems and is referred to as the official release. The final step, *operational success*, consists of two subsequent directions of development: the (substantial) expansion in number of users, and the realization of the first profits.

To mitigate any issues regarding potential survivorship bias, our final sample is a truncated subset of the clustered milestone steps. The truncated sample consists of startups (and their milestones) that either reached the last milestone (operational success) or stopped reporting milestones. The milestone data (description of the milestone and its reporting date) is as of March 31, 2021. If, at this date, more time than the duration of Q3 has passed since the last milestone, it is assumed that the startup has stopped reporting and failed at the last milestone step. The duration between two milestone steps is derived from the startups in the sample. The final milestone sample consists of 3,864 startups reporting at least one milestone. Table 1 shows how many startups reach each milestone step.

[Place Table 1 about here]

For example, 725 or 18.8% of the startups in our sample reach operational success. Conceptually, these ventures would need to have successfully run through all preceding milestones. However, we are not always able to identify all previous milestone steps; e.g., we may be able to capture all milestone steps from the raw data for one startup except the PoC step. This may result from a missing startup update or because our clustering approach did not recognize the reporting as this milestone step. In those instances, we consider missing preceding milestones to be implicitly achieved and add milestone dates based on mean duration between two steps. Overall, our final sample contains 20,431 milestones across all startups. Figure 1 illustrates how the number of reported and implicitly achieved milestones is distributed along the startup life cycle. Reaching operational success is, by design, based on 100% reported data. Interestingly, two phases are predominantly self-reported by startups: the initiation of the venture (*idea*), and the phase in which a startup has reached or is close to reaching a final product that it can launch to broad audience (*MVP* and *full product*). In contrast, the steps PoC and prototype are often not explicitly reported by startups.

[Place Figure 1 about here]

Due to data availability limitations, for some of our analyses we group the seven milestone steps into a higher-level clustering. For example, when assessing the impact of the ICO's timing on longer-term financial measures (e.g., abnormal token returns over a two-year horizon), the number of observations is reduced for PoC and the last two milestones. Therefore, we cluster the first two milestone steps, idea and PoC, into the *ideation* phase and the last two steps, full product and operational success, into a joint cluster called *operational success*. This approach results in five milestone clusters: ideation, prototype, pilot, MVP, and operational success. We explicitly state in which analyses we apply the five clusters instead of the seven milestone steps. It is also worth noting that the matching of several data sources substantially reduces our sample size. For example, our models regarding operational performance are based on approximately 750 startups with non-missing variables. Thus, for all statistics and models, sample sizes vary as we always use the largest sample possible.

3.2 Variable definitions

3.2.1 Operational performance

The extracted milestone steps comprise the basis for our measures of startups' operational performance. We leverage them to define two dummy variables. First, we encode *operational success* as one if a startup has reached the milestone operational success, and zero otherwise. Second, we encode *full product* as one if a startup has reached at least the milestone full product, and zero otherwise.

3.2.2 Financial performance

We evaluate the financial performance of startups along two dimensions. First, consistent with previous research on blockchain-based ventures (e.g., Fisch, 2019), we measure firm valuation at the time of the ICO as the natural logarithm of the total funding amount (in $). Second, we compute buy-and-hold abnormal returns (BHAR) after the initial token listing by subtracting the market index buy-and-hold return from the startup's buy-and-hold return over an identical period

(Fisch and Momtaz, 2020; Lyandres et al., 2022). We utilize a market-capitalization-weighted token benchmark and holding periods of 6, 12, 18, and 24 months.

3.2.3 Independent variables

Irrespective of the analysis focus (operational or financial performance), one of our main independent variables is *crypto fund*. It is a dummy variable that is equal to one if a startup has received CF backing for its ICO, and zero otherwise. Based on the classification by *Crypto Fund Research*, we further define two indicator variables for CF investment strategies (*crypto venture fund* and *crypto hedge fund*). Specifically, a startup is considered to be hedge fund-style backed if it has secured funding from at least one crypto hedge fund. Thus, when analyzing the impact of CF investment strategies, a startup can either be non-backed, venture-style backed, or hedge fund-style backed.

For the assessment of operational performance, *funding amount* is the other key explanatory variable. It is measured as the natural logarithm of the total amount raised during the ICO (in $). Therefore, funding amount serves two purposes across our analyses. First, it is an important independent variable when assessing the drivers of operational success following the ICO. Second, it functions as an outcome variable when determining the influence of CF backing and operational parameters (before the ICO) on firm valuation at the time of the ICO.

For the assessment of financial performance, we focus on two additional groups of explanatory variables. First, we consider the highest milestone reached prior to the to the date of a given financial measure. This is either the milestone that has been accomplished at the time of the ICO (*milestone reached at time of ICO*) or the milestone that has been achieved up to the time of the 6- or 24-month token-holding period in the secondary market (*milestone reached after 6/24 months*). Second, for the financial measures in the aftermarket (6- or 24-month BHAR), we take into account the speed of operational development since the ICO. We calculate the number of milestone steps a startup has completed since the ICO (and before the end of the respective holding period) and define *strong operational development since ICO* as one for top-quartile performers, and zero otherwise.

3.2.4 Control variables

In all models, we use a comprehensive list of control variables encompassing firm, offering, market, and human capital characteristics. All variables are detailed in Table A1 in the Appendix.

3.3 Summary statistics: Outcome variables

Summary statistics for our operational and financial outcome variables as well as their comparison across CF-backed and non-CF-backed startups are presented in Table 2. 18.76% of all startups reach the final milestone of operational success. The second-to-last milestone, full product, is achieved by 49.85% of our sample firms. Regarding financial performance, our average sample startup secures \$2.96 million during the ICO (log = 14.902, log SD = 2.047). In the aftermarket, it generates buy-and-hold abnormal returns of –7.81% (SD = 224.30%), –43.55% (SD = 145.47%), –53.88% (SD = 118.25%), and –54.76% (SD = 79.01%) over the course of 6, 12, 18, and 24 months, respectively.

The comparison of operational and financial performance between CF-backed and non-CF-backed startups shows that CF-backed firms achieve greater financial success while underperforming their non-CF-backed peers on operational measures. Specifically, fewer CF-backed startups reach the milestones full product and operational success (percentage point Δ = –12.89% and –6.57%, respectively). Both differences are statistically significant at the 1% level. However, CF-backed firms raise more capital during the ICO (log Δ = 1.567) and achieve better performance in the secondary market with differences in mean BHAR of 96.68%, 42.09%, 31.56%, and 6.72% over investment periods of 6, 12, 18, and 24 months, respectively. Interestingly, the statistical significance decreases over time. Whereas the difference in funding amounts and BHAR over 6 and 12 months are statistically significant with p-values below 1%, the significance of 18-month BHAR falls to the 5% level, and over 24 months the difference is no longer significant.

[Place Table 2 about here]

3.4 Summary statistics: Operational characteristics, crypto fund backing, and control variables

Summary statistics for operational characteristics, CF backing, and all control variables are reported in Table 3. The average sample startup conducts the token-based crowdfunding after 2.9 (SD = 1.6) milestone steps, indicating that the ICO takes place right before the prototyping phase is completed. On average, startups reach 4.1 (SD = 1.6) and 5.3 (SD = 1.4) milestones at the time of the 6- and 24-month BHARs, respectively. This corresponds to having achieved the piloting and MVP milestones after 6 and 24 months in secondary market trading. Concerning operational development, the average firm accomplishes 1.3 (SD = 1.2) and 2.7 (SD = 1.8) milestone steps during the 6 and 24 months following the ICO, respectively.

Of all startups, 5.6% secure CF financing. Broken down by CF investment strategies, 3.1% of startups receive capital from crypto venture funds, whereas 1.7% are backed by crypto hedge funds.

On average, our sample firms achieve an overall expert rating on *ICObench* of 3.0 (SD = 0.7), *GitHub* open-source code is published in 54% of all cases, a platform business model strategy is pursued by 57% of all ventures, the average startup targets 3.0 (SD = 2.4) different industries, and 87.6% of the startups' underlying blockchain technology is built upon the Ethereum standard.

With regard to the token offering, 53.5% of all startups hosted a pre-sale prior to the ICO for which 45.7% established a know-your-customer (KYC) process. Of all ICOs, 8.2% and 31.0% are promoted with bonus and reward schemes, respectively. The average ICO faces 842 competing offerings (SD = 490). Concerning market characteristics, 18.8%, 61.2%, and 20.0% of our sample ICOs occur during the bull, bear, and sideways market cycle, respectively. The average market volatility during the ICO is 11.9% (SD = 5.1%).

The mean team size of our sample ventures is 11.3 members (SD = 7.2). Among the teams, 83.8%, 35.8%, and 84.6% include members with a technical degree, a PhD, and prior crypto experience, respectively.

[Place Table 3 about here]

3.5 Correlations

Pairwise correlation coefficients for all outcome, independent, and control variables are presented in Table A2 in the Appendix.

3.6 Stylized facts

This section examines (i) the duration to reach each milestone, (ii) startup survival rates, and (iii) the impact of the ICO's timing on financial success. Figure 2 shows the cumulative duration to reach each milestone after the idea (the first milestone). The boxes correspond to the range of durations between the lower and upper quartiles; the dot and the mid-hinge indicate the mean and median durations, respectively. Starting from the idea, the average startup takes 10 months to develop the proof-of-concept, soon followed by the setting up of the prototype. The piloting phase is, on average, completed after 16 months and the milestones MVP and full product are subsequently reached in short time intervals of 2 and 3 months after the pilot, respectively. The final milestone, operational success, is achieved after 25 months by the average startup. Two features are noteworthy. First, the inter-quartile range (IQR) indicates that operational development does not follow a narrow time table, but rather a broad range of paths and timelines. For example, the IQR spans from 15 to 33 months for operational success. Second, the operational life cycle suggests that three larger development steps exist: (i) from idea to PoC, (ii) between prototype and pilot, and (iii) from full product to operational success. Overall, the average sample firm that is successful along all milestones requires roughly two years to achieve operational success.

[Place Figure 2 about here]

Figure 3 shows survival probabilities along the startup life cycle. Panel A displays the Kaplan-Meier curve for startup survival over time, Panel B displays the curve along the milestone steps (E. L. Kaplan and Meier, 1958). Regarding survival over time, Panel A indicates that the largest drop in survival rates occurs around 1.5 years following the venture's idea. For example, whereas survival probabilities are relatively high at 81% after 12 months, the rate drops to 34% after 24 months. Once this apparently difficult period is weathered, the risk of business failure increases at a substantially slower pace. While survival rates drop to 17% after 3 years, the chance of survival is

10%, 7%, and 3% after 4, 5, and 6 years, respectively. Thus, the decline in survival rates slows over time, but at low levels. Considering survival rates along the seven milestones, Panel B shows that the biggest declines materialize between the steps pilot, MVP, and full product. The probability of surviving the pilot phase is 84%, but drops to 20% at the full product stage, suggesting that the largest operational challenges need to be solved in the second half of the startup life cycle. In our models regarding operational performance, presented in section 4.1, we examine the underlying drivers of survival rates.

[Place Figure 3 about here]

Table 4 provides a preliminary view of the interaction between operational characteristics and financial success. Specifically, it compares financial performance along the operational timing of ICOs. Panel A shows how financial indicators differ depending on the ICO's timing relative to the completion of operational milestones. Panel B reports the differences in selected means. For example, while the mean funding amount is \$3.02 million (log = 14.92) for ICOs that take place after the ideation phase (idea and PoC), firm valuation increases to \$3.69 million (log = 15.12) after the pilot phase, and drops again to \$3.11 million (log = 14.95) for the milestones full product and operational success. An identical pattern can be observed for all BHAR measures in the secondary market. Therefore, this table provides a first indication of an optimal timing of ICOs. We assess this relationship, among others, in greater detail with our models regarding financial performance in section 4.2.

[Place Table 4 about here]

3.7 Empirical design: Frailty approach, endogeneity, and identification strategy

One key component of our empirical analysis evaluates the drivers behind startups' operational performance, especially the role of CF backing and the capital raised during the ICO. For this assessment, we leverage the two variables *operational success* and *full product* to derive two time-to-event variables. Specifically, the dummy *operational success* combined with the time in days since the idea to either reach this milestone or to terminate the business beforehand is used to define the first time-to-liquidation variable. The dummy *full product* is utilized analogously to construct the second time-to-liquidation variable. Based on the study by Momtaz (2021b), frailty models (Cox Proportional Hazards model with random effects) best fit this kind of time-to-event analysis for the following reasons.

As with most quantitative entrepreneurship research, our sample includes different clusters (e.g., startups are headquartered in various countries, tokenized crowdfunding campaigns are conducted at self-chosen dates); however, the data is used to deduce cross-cluster conclusions. This requires that outcome variables for startups from different groups match if their observed characteristics are identical. Due to unobserved heterogeneity in startup data, this assumption does not hold in the vast majority of cases. It is therefore essential to properly account for unobserved heterogeneity, which might otherwise lead to complicated biases in time-to-event estimations. Frailty models, first introduced by Vaupel et al. (1979), are better suited to minimize these biases compared to Cox Proportional Hazards models with and without fixed effects (Momtaz, 2021b). Thus, our analyses on operational performance rely on frailty models to estimate the impact of CF backing and funding amount on the two time-to-liquidation variables.

4 Empirical Results

4.1 Operating performance

4.1.1 Time-to-liquidation: Main results

Table 5 presents our regression results for the effect of CF backing and the capital raised on startups' operational performance. Specifically, the main dependent variables measure startup failure as time-to-liquidation events: In Models 1 and 4, the liquidation event is defined as the shortfall to achieve the milestone operational success, encoded as one if the milestone is not reached, and zero otherwise. Time is measured in days from the milestone idea until the venture is terminated or operational success is achieved. In Models 2 and 5, the liquidation event is based on the achievement of the milestone full product. We leverage the two milestones as reference points for failure in order to ensure that our results are robust to the clustering of the underlying raw milestone data. For the time-to-event models (Models 1, 2, 4, and 5), we apply the frailty approach as outlined in section 3.7.

In our baseline regressions, Models 1 and 2, we estimate the impact of CF backing and funding amount on time-to-liquidation. Model 3 shows the funding model, in which the funding amount—defined as the natural logarithm of the capital raised during the ICO (in $)—is a function of CF backing and all control variables. The underlying model is an OLS regression. The residuals of Model 3 are considered as excess funding (positive or negative). Models 4 and 5 replicate the approach of Models 1 and 2, but specifically test for the impact of excess funding as derived from Model 3. In all models, we control for our comprehensive set of firm, offering, market, and human capital characteristics. The frailty and OLS models include random and fixed effects on the country level and quarter-year level, respectively.

Three features are worth noting before we assess the impact of individual variables. First, the number of observations slightly differs between the frailty model based on the milestone full product and the model based on operational success. This is a result of the timing of the ICO; to assess the impact of funding on operational performance, at least one milestone needs to be achieved after the ICO is conducted. Thus, when considering the milestone full product as the liquidation event, the token-based crowdfunding needs to be completed earlier, leading to a marginally smaller sample. Second, the coefficient estimates in all frailty models are reported as hazard ratios (exponentiated regression coefficients) for easier interpretation. For example, with regard to CF backing, the hazard ratio defines the probability of liquidation of a backed venture relative to a non-backed startup over a given time interval. Thus, a number greater than one indicates a comparatively higher risk, whereas a number less than one indicates a lower risk of business failure. Third, the log-likelihood ratio tests show that all frailty models are significant with varying p-values, but at least below the 10% level.

The first key finding of Table 5 is that all frailty models suggest that CF backing shortens a startup's time-to-liquidation, confirming Hypothesis 1. The hazard ratios for the CF dummy variable range from 1.235 to 1.424 with statistical significance at the 5% and 10% level, depending on the model. For example, the hazard ratio of 1.243 for CF backing in Model 1 indicates that the presence of a crypto fund decreases the average time-to-liquidation by 24.3%, all else equal. Hence, for a given time interval, CF backing increases the risk in building an operationally sound business. The second key finding relates to the capital raised during an ICO. In contrast to the role of crypto funds, Models 1 and 2 suggest that the funding amount increases the time-to-liquidation, statistically significant with p-values below 5%. The hazard ratios of 0.895 and 0.864 indicate that, for example, 10% of additional funding is at least associated with a 1.1% increase in the average time-to-liquidation, holding all other parameters constant.[5] Therefore, the amount of funds secured via the ICO boosts the odds of operational success.

Models 4 and 5 test whether the positive impact of funding is solely driven by its total amount or also by the delta relative to the expected amount. Thus, in column (3), we first model the expected capital raised based on all variables and find a few strong predictors. Specifically, CF backing, the expert rating, and the team size show a significantly positive impact, while the publication of source code on GitHub has a significantly negative effect. Interestingly, the direction of influence for the latter three variables (expert rating, team size, and source code on GitHub) is identical between the operational models in columns (1) and (2) and the financial model on funding in column (3). However, the impact of CF backing is reversed and significant in both performance areas. Models 4 and 5 show that not only the funding amount but also the excess capital raised have a significantly positive impact on operational performance. The hazard ratios of 0.886 and 0.844, with p-values below 5%, are similar to those in Models 1 and 2, but indicate a slightly more pronounced effect.

Across the operational models in Table 5, most of our controls exhibit weak explanatory power. Only a know-your-customer (KYC) process and the team size consistently increase the average time-to-liquidation in all models, while an interaction term between team size and funding amount consistently shows a negative influence. We add this interaction term to account for any potential interconnection between the two variables. In particular, the impact of the funding amount (and thus the opportunity to acquire more external resources via this capital) may be less relevant if a larger team (and thus a broad and deep range of internal expertise) supports the venture. In Models 2 and 5, two additional variables are both relevant and statistically significant. Similar to the funding model, the publication of source code on GitHub is negatively associated with time-to-liquidation, whereas the use of the Ethereum standard shows a positive effect.

Overall, the results in Table 5 indicate that CF backing has a significantly negative impact on the operational performance of startups, while both the capital raised and excess funding have a

[5]Derivation of the economic impact for the log funding amount: $0.989 = e^{(log(1.1) \times log(0.895))}$ where 0.989 is the hazard ratio of a 10% increase in absolute $-values, resulting in the 1.1% increase in time-to-liquidation. Log(1.1) converts the additional funding from absolute $-values to log values and log(0.895) derives the respective regression coefficient from the hazard ratio.

significantly positive effect.

[Place Table 5 about here]

4.1.2 Time-to-liquidation: The role of investment strategies

Table 6 presents how investment strategies of crypto funds (venture- vs. hedge fund-style) influence the operational performance of startups. All models are analogous to those introduced in Table 5, with the difference that the variable for CF backing is replaced by the dummies for investment strategy. Hence, Models 1 and 2 test the impact of investment strategy and the total capital raised, and Models 4 and 5 assess the influence of investment strategy and excess funding. Because the coefficients of the control variables are consistent with those reported in Table 5, we suppress the estimates for the sake of brevity.

Regarding investment strategy, all frailty models suggest that the adverse effect on operational performance is driven by hedge fund-style crypto funds. Although both venture- and hedge fund-style strategies show hazard ratios above one, only those of crypto hedge funds are statistically significant at the 5% and 10% level, depending on the model. The hazard ratios for the hedge fund-style dummy range from 1.390 to 1.730, indicating that backing by a crypto hedge fund can decrease the average time-to-liquidation by as much as 73.0%, all else equal. For funding and excess funding, the analyses paint a picture that is comparable to the results in Table 5, with hazard ratios showing only minor discrepancies.

These results confirm two of our assumptions. First, they support that the capital raised (the total funding amount, but also excess funding) increases the average time-to-liquidation and thus positively influences operational performance. Second, the negative effect of crypto funds on the average time-to-liquidation is driven by crypto hedge funds. Our results suggest that their backing severely impacts the longer-term operational success of a blockchain-based venture. Below, we assess how the influence of crypto funds and their investment strategies compare to measures of financial performance.

[Place Table 6 about here]

4.2 Financial performance

4.2.1 Funding and aftermarket returns: The role of crypto funds

Table 7 shows our regression results for the effect of CF backing on startups' financial performance. In order to assess the short-term and long-term financial impact of CFs, we use three dependent variables: the venture valuation at the time of the ICO, measured as the natural logarithm of the total funding amount (in $); the BHAR over 6 months; and the BHAR over a period of two years. The models in Panel A test the influence of CF backing, while the models in Panel B disentangle the effect of crypto fund investment strategies. We control for an extensive list of variables. First, we include a set of factors related to the operational development and the timing of the ICO. Second, in accordance with the analyses of operational performance, we incorporate all firm, offering, market, and human capital characteristics. Third, we add the funding amount as control variable for the secondary market models to be consistent with the operating models. Country and quarter-year fixed effects are always incorporated. The explanatory power of our models, with adjusted R^2 values ranging from 20.7% to 36.3%, corresponds to existing empirical research in the field of blockchain-based startups (Fisch and Momtaz, 2020; Lyandres et al., 2022).

Comparing the sample size across models, it is noteworthy that the number of observations reduces considerably from the valuation models (978 startups, columns (1) and (4)) to the aftermarket models for 6-month and 24-month BHARs (354 and 230 firms, respectively, in columns (2) and (5), and (3) and (6)). The reasons for this are twofold. First, many startups have not had their tokens listed on a secondary market exchange for the respective holding periods at the time of our data collection. Second, the inclusion of operational characteristics before and after the ICO further reduces the samples. The remainder of this section focuses on the role of crypto funds, and section 4.2.2 describes the impact of CF investment strategies.

The regression results in Panel A confirm Hypothesis 2 that crypto funds demonstrate a significantly positive influence on short-term financial metrics of their backed firms. In Model 1, the coefficient for the CF dummy of 0.935, with a p-value below 1%, indicates that a token investment of a crypto fund during the ICO increases the firm valuation by more than 150% ($\approx e^{0.935} - 1$). Thus, the immediate impact is highly significant not only in statistical terms, but also economically. The positive influence of CF backing remains unchanged and statistically significant at the 5% level for BHAR over 6 months. For this holding period, ventures with CF backing achieve abnormal returns that are 25.4 percentage points higher than their non-backed peers, all else equal. This effect, however, changes when considering a holding period of 24 months. For this time frame, the CF coefficient stays positive, but is substantially lower at 0.070 and is no longer statistically significant.

Similar to our operational analyses, the vast majority of the controlling factors are not significant predictors for the financial measures in Panel A. Two variables are particularly notable: the expert rating and the number of team members have a positive impact (statistically significant at least at the 5% level) in two of the three models.

Overall, the results suggest that crypto funds act as myopic investors in the market for blockchain-based startups. This investment behavior explains why their impact is statistically and economically only significant for the short-term financial variables, but vanishes over the long term. In non-tabulated robustness tests, we find that the impact (size of coefficient as well as the statistical significance) of CF backing gradually decreases in the aftermarket. The coefficient estimates for 12-month and 18-month BHARs fall between the estimates for the 6-month and 24-month BHARs and the respective p-values steadily increase.

[Place Table 7 about here]

4.2.2 Funding and aftermarket returns: The role of investment strategies

The split by investment strategy in Panel B of Table 7 suggests that, while venture- and hedge-style CFs have a significantly positive impact on short-term financial measures, hedge fund-style strategies appear to be the driving force. The CF investment strategy estimates in Model 4 are 0.843 and 1.147 for venture- and hedge-style funds, respectively. Both coefficients are highly statistically significant, with p-values below 1%. The estimates indicate that a venture-style approach increases the capital secured during the ICO by 132%, and a hedge fund-style approach by 215%. Hence, although both effects are statistically and economically significant, the impact of crypto hedge funds is even higher by 83 percentage points. A similar gap is prevalent for BHARs over 6 months. The venture-style coefficient is 0.218, statistically significant at the 10% level. This compares to a hedge fund-style coefficient of 0.752 with a p-value below 1%. Consequently, although the impacts of both approaches remain significant, the effect of hedge fund-style backing is substantially higher in statistical and economic terms. Model 6 reiterates the view on the long-term influence of CFs as described for Panel A. The coefficients for venture- and hedge fund-style strategies drop in absolute values compared to Model 5 and become statistically insignificant. The impact of the control variables is largely unchanged compared to the observations in Panel A.

The influence of CF backing, which decreases over time, is reiterated in Figure 4. It shows the impact of the two CF investment strategies on startups' token price performance in the secondary market. Panels A and B depict the influence of crypto venture funds and crypto hedge funds, respectively. Each graph reports the regression coefficients on BHARs over holding periods from 6 to 24 months. All coefficients are estimated based on regression analyses that follow the model structure as presented in columns (5) and (6) of Table 7. This figure illustrates two key findings. First, the impact of CF backing on short-term abnormal aftermarket returns is mainly the result of hedge fund-style strategies. Second, the high influence of crypto hedge funds is concentrated on the short-term, as their regression coefficients drop substantially over the 12- and 18-month holding periods.

[Place Figure 4 about here]

In addition to these findings, Figure 5 provides graphical evidence of the pathway by which crypto hedge funds likely exert their short-term impact on startups' financial performance. The figure shows startup backing of CF investment strategies across token liquidity quartiles. Token liquidity, in $ (log), is measured as a token's cumulative trading volume over the 6-month BHAR holding period. Split by investment strategy, the figure shows the share of CFs in each liquidity quartile. For crypto venture funds, the share of funds ranges from 16% to 36% per quartile. Thus, their backing is fairly homogeneous across the liquidity distribution. For crypto hedge funds, the picture looks different. While the share of their backing ranges from 3% to 12% in the lower three quartiles, 78% of their backed ventures rank in the fourth quartiles. Hence, crypto hedge funds focus their token investments on startups that are likely to experience high trading volumes in the secondary market. The high level of liquidity may allow crypto hedge funds to push their agenda via a more credible threat of exit, as discussed extensively in existing literature on equity markets (e.g., Döring et al., 2021; Hirschman, 1970).

[Place Figure 5 about here]

This set of analyses indicates that the myopic investment behavior of CFs is primarily driven by hedge fund-style strategies. Combined with the stylized facts on survival over time (e.g., Figure 3) and the assessment of operational performance (Table 5 and 6), the results suggest that blockchain-based startups require more time to build an operationally successful business than the investment periods of CFs allow, especially of crypto hedge funds. These funds may still exert influence on the ventures' operations, however, with the intention to drive short-term financial results instead of longer-term operational success.

4.3 Optimal timing for token offering

In this section, we assess whether an optimal timing exists for startups to raise capital via an ICO. Table 8 reports the results for the impact of the ICO's timing and other operational achievements on short- and long-term financial outcomes. Specifically, the following operational characteristics are the focus: (i) the milestone reached at the time of the ICO; (ii) the milestone reached before the end of the respective holding period in the secondary market, thus either 6 or 24 months depending on the financial dependent variable; and (iii) a dummy variable indicating whether a startup experienced strong development between the ICO and the respective holding period. Detailed descriptions of these variables can be found in section 3.2 and Table A1 in the Appendix. The models, dependent variables, and controls follow the setup in Table 7.

To test for an (inverted) U-shaped relationship between the timing of the ICO and our dependent financial variables, we follow the approach as outlined by Haans et al. (2016) and Lind and Mehlum (2010). Thus, all our regression models include the variable *milestone reached at time of ICO* as well as its squared term. For the aftermarket models, we include the interaction term between the milestone reached at the respective holding period and the indicator variable for strong development. This term is added to account for a possible interdependency between the two variables. For example, strong operational development may be less relevant if a startup has become operationally successful, overshadowing the speed of the development. Likewise, if a startup is at an earlier point in the operational life cycle at the respective holding period, strong operational development may be a more relevant proxy to gauge future success.

The results across Panels A and B suggest that, for short-term financial measures, a perfect point in time exists (relative to the startup's operational milestones) to conduct the blockchain-based crowdfunding, consistent with Hypothesis 4. In Model 1, the coefficient for ICO timing is positive and significant (p-value below 5%) and its squared term is negative and significant (p-value below 10%). These results indicate that the timing of the ICO and the capital raised have an inverted U-shaped relationship. Specifically, the coefficient estimates pinpoint the perfect ICO timing as being right after the completion of the piloting milestone cluster ($3.19 = 0.372/(-2 \times -0.058)$). The presence of the inverted U-shaped relationship is confirmed by the three requirements described by Haans et al. (2016) and Lind and Mehlum (2010). First, the quadratic term of *milestone reached at time of ICO* shows the expected sign and is significant. Second, the partial derivative for the funding amount with respect to the ICO's timing is positive and significant for the earliest possible timing, and negative and significant for the latest possible timing. The ICO can be conducted at the earliest after the ideation (*milestone reached at time of ICO* $= 1$) and at the latest following the operational success cluster (*milestone reached at time of ICO* $= 5$). Thus, the slope is 0.25 ($= 0.372 + 2 \times -0.058 \times 1$) and –0.21 ($= 0.372 + 2 \times -0.058 \times 5$) for the earliest and latest possible timing, and both values are significant with p-values below 5% and 10%, respectively. Third, the turning point with a value of 3.19 lies between the mean and median ICO timings for the corresponding sample of 978 startups (2.20 and 4.00, respectively) and is thus well within the earliest and latest possible ICO timings. As an additional robustness check suggested by Haans et al. (2016), the cubic term of *milestone reached at time of ICO* is not significant when added to Model 1, further demonstrating that the relationship is U-shaped and not potentially S-shaped. Taken together, the results of Model 1 suggest that the relationship between the timing of the ICO and the funds raised follow an inverted U-shaped curve.

Model 2 confirms this shape of relationship for abnormal returns over a 6-month holding period: (i) The quadratic term of ICO timing is negative (p-value below 5%), (ii) the slopes at the low and high end of potential ICO timings show the expected sign and are significant (both at the 5% level), and (iii) the turning point as well as its 95% confidence interval are located within the data range. The turning point at 2.98 indicates that the optimal timing of the ICO with regard to 6-month BHAR is right before the completion of the piloting milestone cluster and thus is fairly similar to the optimal timing to raise the highest possible amount of capital during the ICO. Apart from ICO timing, the results of this model suggest that operational development following the ICO becomes a relevant, positive driver that is statistically significant at the 10% level. Interestingly, the interaction term between strong operational development and the milestone reached up until the 6-month BHAR shows that the impact of the speed of operational progress decreases over the course of the startup life cycle.

For our long-term financial measure, the effect of the ICO's timing disappears while the importance of the operational development stays intact. Model 3 shows that neither the linear nor the quadratic term for the timing of the ICO shows any statistical significance with regard to 24-month BHAR. However, superior speed in operational development remains a driving force, but its impact is declining with the achievement of higher operational milestones. The models in Panel B, in which the operational characteristics stay unchanged and only the CF dummy variable is replaced with the indicators for CF investment strategies, confirm the results of Models 1 to 3 in Panel A.

Consequently, the operational characteristics in Table 8 suggest that there exists an optimal timing to conduct an ICO, and that this is around the completion of the piloting milestone. This finding is highly relevant for startups and crypto funds because (i) the amount of capital raised drives operational success (as indicated by our analyses on operational performance) and (ii) the ICO's timing impacts short-term abnormal returns in the secondary market. For financial measures in the aftermarket, the effect of the ICO's timing decreases with longer holding periods, while the speed of operational development becomes a relevant factor and should thus be closely monitored by crypto funds.

[Place Table 8 about here]

Table 9 presents how the impact of the ICO's timing and operational development differs for startups with and without CF backing. Specifically, Panel A measures the effect for the subsample of startups with CF backing, while Panel B displays the models for the set of ventures without such backing. Apart from the sample split, the model components mirror those reported in Table 8.

The models in Panel A show that the inverted U-shape is present and significant for 6-month BHAR. For this holding period, (i) the quadratic term of ICO timing is negative (p-value below 5%), (ii) the slopes at the low and high end of potential ICO timings have the expected sign and are significant (at the 5% and 10% level, respectively), and (iii) the turning point is located well within the data range. Other operational characteristics show no significance. For Panel B, the inverted U-shaped relationship is found for the funding amount during the ICO. The linear and quadratic terms of the milestone reached at this time are of the expected signs and significant at the 5% level. The additional tests (slope of low and high end of possible ICO timings; location of optimal point) confirm the assumed shape. Similar to Panel A, other operational indicators do not consistently reveal significant effects on financial performance.

The combined results of Panels A and B show that the optimal timing of the ICO is around the piloting phase, and is particularly relevant to maximizing funding from crowd investors. The findings also indicate that ICOs at this point in the operational life cycle are also best suited for crypto funds to benefit in the short-term (6 months) from their certification of venture quality.

[Place Table 9 about here]

5 Discussion and Conclusion

5.1 Summary of main results

This paper tests three overarching hypotheses. Hypothesis 1 posits that institutional investor-backed ventures that conduct ICOs have *poorer* operating performance than solely crowdfunded ICO ventures, while Hypothesis 2 posits that investor-backed ICO ventures have *stronger* financial performance than solely crowdfunded ICO ventures. Moreover, Hypothesis 3 and Hypothesis 4 suggest that there are two inverted U-shaped relationships: one between the fundraising success of ICO ventures and their life cycle, and another between the short-term financial performance of ICO ventures and their life cycle. We test these hypotheses using the *Token Offerings Research Database* (*TORD*), which provides the best data coverage for ICOs conducted up to the end of 2021, and a hand-collected sample of 20,431 operational milestones reported by *TORD* ventures. The empirical context of ICOs offers a nearly ideal laboratory to test these predictions because, unlike non-token-based (e.g., equity or reward-based, Ahlers et al., 2015; Vismara, 2016) crowdfunding, the market for tokens is highly integrated in terms of investor type (i.e., individual and institutional investor types), which suggests a straightforward empirical research design to test Hypothesis 1 and Hypothesis 2, and in terms of the startup life cycle stage at which a venture conducts an ICO (ranging from ideation to functional product stages and beyond) (Bellavitis et al., 2020; Bellavitis et al., 2021; Fisch, 2019; Howell et al., 2020; Huang et al., 2020; Momtaz, 2020), which provides variation across the startup life cycle to test Hypothesis 1.

The empirical results provide support for all three hypotheses. For Hypothesis 2, we find that institutional investor backing shortens a startup's time-to-liquidation. For example, the smallest hazard ratio of 1.235 with statistical significance at the 5% level suggests that the presence of an institutional investor decreases the average time-to-liquidation by 24.3%, all else equal. We find a coefficient on the dummy for institutional investor backing of 0.935, with a p-value below 1%, suggesting that institutional investor backing during the ICO increases firm valuation by more than 150% ($\approx e^{0.935} - 1$). The positive influence of institutional investor backing remains unchanged and statistically significant at the 5% level if we test BHAR over 6 months after the token exchange listing. For this holding period, ventures with institutional investor backing achieve abnormal returns that are 25.4 percentage points higher than their non-backed peers, all else equal. For Hypothesis 3 and Hypothesis 4, following the practical guidelines set forth by Haans et al. (2016) for testing U-shaped relationships, we estimate that the optimal ICO timing, as measured by both the funding amount and the six-month BHAR, is around the completion of the piloting milestone.

Overall, these results suggest that institutional investors might indeed be using their reputations to drive up valuations and quickly exit the company after the ICO; an empirical pattern that we term *certification arbitrage*. More precisely, we find that institutional investors only increase portfolio ventures' financial performance in the short run when certification arbitrage is at play; however, we do not find a significant positive effect of professional investor backing on ventures' financial performance in the long run. Our results are robust to endogeneity concerns related to observed and unobserved heterogeneity in our sample, and are insensitive to various modifications of our empirical baseline model. More importantly, given that we are the first to compile a representative sample of operating milestones in a crowdfunding segment, we are able to produce a number of stylized facts about the actual product-market performance of crowdfunded firms, which we elaborate on next.

5.2 Theoretical contributions and practical implications

Our study contributes to the entrepreneurial finance literature in several important ways. First, we develop a theory of certification arbitrage whereby the engagement of institutional investors can be harmful for the operating performance of ventures that tap capital markets via an ICO. We therefore depart from the notion upheld in previous research (e.g., Fisch and Momtaz, 2020; Hsu, 2004) that certification of institutional investors positively affects venture performance. Certification arbitrage arises when institutional investors, who attest to the quality of the company with their funding, have a short-term incentive to exit as long as token valuations are favorably impacted by their certification. While institutional investors are tied to their investments for years in traditional entrepreneurial finance markets due to the illiquidity of startup markets and contractually defined lock-up periods (Cumming, 2008; Cumming et al., 2005; Cumming and Johan, 2013), our theory of certification arbitrage is specific to the novel markets of tokenized ventures (for recent reviews of the ICO market, see Alshater et al., 2023; Brochado and Troilo, 2021). Second, our findings contribute more specifically to the recent literature on investor choice in entrepreneurial finance (e.g., M. Colombo et al., 2021; Fisch and Momtaz, 2020; Momtaz, 2022a). While it is known that specialized venture capital funds are well equipped to support ventures in their early stages (e.g., Bertoni et al., 2011; M. Colombo and Grilli, 2010; Hsu, 2004), little is known regarding *when* precisely they should enter during the life cycle of early-stage startups. Our results suggest that there are inverted U-shaped relationships between the ICO timing over the ventures' life cycle and (i) the fundraising success of ICO ventures and (ii) short-term financial performance. Although surely not conclusive, these findings offer building blocks for further theorizing around investor choice in entrepreneurial finance markets.

In addition to these theoretical contributions, our comprehensive data collection, which includes more than twenty thousand operational milestones reported by ICO ventures, offers new stylized facts about the performance and survival of crowdfunded firms. These stylized facts are valuable given that Böckel et al. (2021, p. 433) summarize in their comprehensive review of the crowdfunding literature that there is a major "research gap related to the post-funding phase" and, similarly, Vanacker et al. (2019, p. 237) conclude that the post-funding performance of crowdfunded firms is probably the "least explored" topic in entrepreneurial finance. We document the following post-funding patterns: First, only every other ICO venture ultimately develops a full product and only 19% reach the stage of operational success. Second, conditional on achieving this milestone, startups that develop a full product take about 19 months and startups that are operationally successful take about 24 months from ideation to reach this stage. Third, the most common reasons why startups fail are that they are not able to develop their pilot into a minimum viable product or their minimum viable product into a full product, with more than 60% of all startups failing during the stages from pilot to full product development.

Our study also has several implications for practice. For policymakers, certification arbitrage is a regulatory blind spot and may call for a more nuanced legislative approach. While certification arbitrage with *security* tokens bears all the marks of an illegal pump-and-dump scheme, certification arbitrage with *utility* tokens takes place in a legal gray area and illegality depends, among other things, on the specific intention of the investor, which can be difficult to prove. Our theoretical insights and empirical results raise new questions for the regulation of ICOs. Policymakers and regulators will need to reassess to what extent it makes sense to distinguish between security and utility tokens when the nature of market manipulation is very similar and utility tokens are tradable just like security tokens in public markets. For entrepreneurs, our findings have important implications for investor choice and the timing of crowdfunding campaigns. Founders often try to get any investor on board just to keep going. However, especially in tokenized markets, it is important that investors are selected strategically by founders, as they can influence both a venture's operating performance and its financial performance. It is also crucial to determine when capital is to be raised, because raising capital too early or too late can lead to underfunding and thus also affect the company's success. Even if the pilot milestone is the optimal time to raise capital via an ICO, as estimated in our study, the discussions with investors, platforms, and advisors must undoubtedly start months earlier so that the ICO can be optimally timed.

5.3 Limitations and potential avenues for future research

Our study represents a first step towards understanding how the tokenization-induced liquidity of entrepreneurial finance markets changes the nature of startup financing and performance that matter for entrepreneurs, investors, and policymakers alike. Given the vast and growing interest in markets for tokens, as evidenced by the large number of recent reviews (e.g., Alshater et al., 2023; Brochado and Troilo, 2021), and the necessarily high level of abstraction in our analysis, it seems very likely that a vivid literature concerning the liquidity aspects of tokenized venturing will soon emerge.

While our study does not claim that all CFs engage in illegal or legal gray-area activities through certification arbitrage, future research will need to address the question of how to differentiate value-adding backers and purely myopic institutional investors. We have provided a first rough answer to this question by distinguishing between crypto hedge and crypto venture funds, with hedge fund-style investors being more likely to engage in myopic behavior. Alternative regulatory measures from venture capital and traditional IPO literature—such as contractual lock-up periods and investor protection against market manipulation (e.g., Cumming, 2008; Cumming and Johan, 2013)—will very likely have to be adapted for ICOs in the future, even if they are considered utility tokens. Otherwise, the new tokenized venture market threatens to collapse before the technology can be fully exploited for financial markets (Momtaz, 2021c). Future research will therefore have to be interdisciplinary, bringing technology together with scholarship in business, economics, and law.

5.4 Concluding remarks

Alongside technological innovation, ICOs have made the market for entrepreneurial finance more liquid. Although liquidity is often seen as an advantage for retail investors in particular (Diamond and Verrecchia, 1991), this paper argues that liquid markets for startups may pave the way for a new form of moral hazard through *certification arbitrage*. Our theoretical arguments and empirical findings call for policymakers to address this regulatory blind spot to make entrepreneurial finance markets for tokenized startups more efficient.

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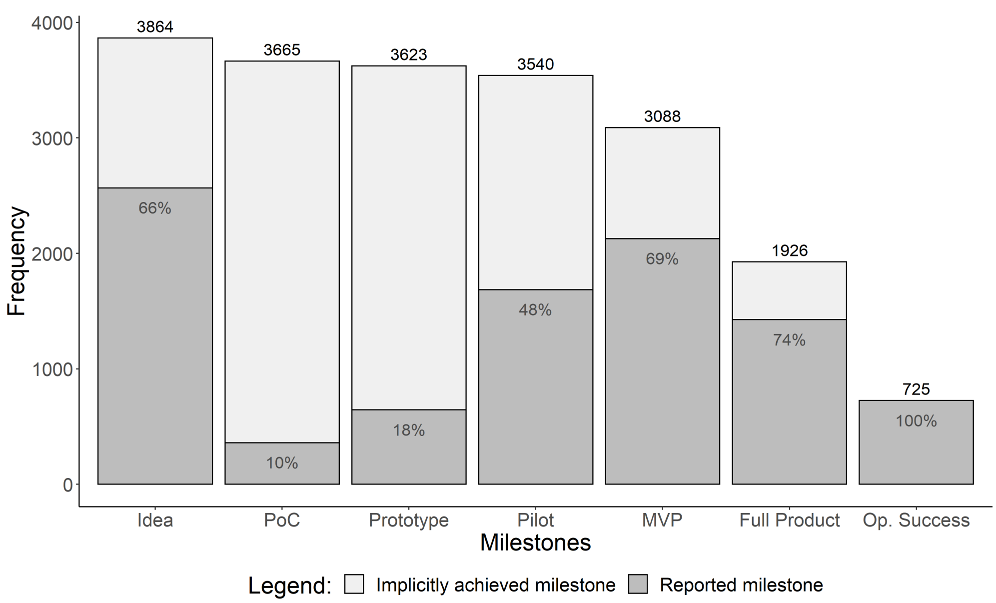
Figures and Tables

Table 1: **Sample Distribution**

	N
Aggregate Numbers:	
Total # of blockchain-based startups with at least one milestone	3,864
Total # of milestones across all startups	20,431
# of Startups per Milestone:	
Idea	3,864
Proof of Concept (PoC)	3,665
Prototype	3,623
Pilot	3,540
MVP	3,088
Full Product	1,926
Operational Success	725

Note: The number of milestones includes ones that are either reported by the startup or that are implicitly achieved (with imputed dates) based on the reported milestones for our truncated sample. The truncated sample consists of startups (and their milestones) that either reached operational success or stopped reporting milestones. Specifically, The milestone data is as of March 31, 2021. If at this date more than the Q3 duration has passed since the last milestone, it is assumed that the startup has stopped reporting and failed at the last milestone step.

Figure 1: **Startups and Operational Milestones: Sample Distribution**



Note: This figure plots the number of startups that have reached each milestone. Per step, the share of reported and implicitly achieved milestones are displayed. Implicitly achieved milestones are steps that occur before that last reported steps, but have not been reported or captured.

Table 2: **Operational and Financial Performance: Summary Statistics**

Panel A: All Startups			
	Mean	*SD*	*Median*
Operational Performance:			
Startup reached operational success, in %	18.76	39.05	0.00
Startup reached at least full product, in %	49.85	50.01	0.00
Financial Performance:			
Funding amount, in $ (log)	14.902	2.047	15.202
6-month BHAR, in %	-7.81	224.30	-43.02
12-month BHAR, in %	-43.55	145.47	-69.80
18-month BHAR, in %	-53.88	118.25	-57.88
24-month BHAR, in %	-54.76	79.01	-50.84

Panel B: CF- vs. Non-CF-backed Startups			
	Mean CF-backed	*Mean Non-CF-backed*	*Δ in Means: CF – Non-CF*
Operational Performance:			
Startup reached operational success, in %	12.56	19.13	-6.57***
Startup reached at least full product, in %	37.67	50.56	-12.89***
Financial Performance:			
Funding amount, in $ (log)	16.272	14.705	1.567***
6-month BHAR, in %	67.01	-29.67	96.68***
12-month BHAR, in %	-11.97	-54.05	42.09***
18-month BHAR, in %	-30.88	-62.44	31.56**
24-month BHAR, in %	-50.00	-56.72	6.72

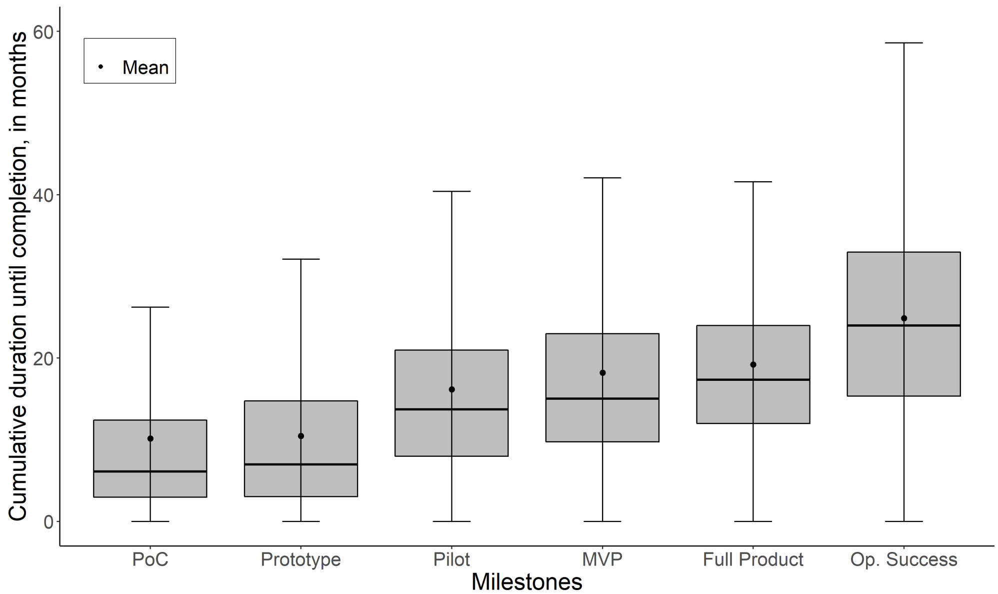
Note: This table reports summary statistics for our operational and financial outcome variables. Panel A presents the performance across all startups. Panel B compares the measures between CF-backed and non-CF-backed startups. The buy-and-hold-abnormal return (BHAR) measures are calculated using a value-weighted token market benchmark. All variables are defined in Table A1. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 3: **Operational Characteristics, Crypto Fund Backing, and Control Variables: Summary Statistics**

	Mean	SD	Q1	Median	Q3
Operational Characteristics:					
Milestone reached at time of ICO	2.911	1.617	1	3	4
Milestone reached 6 months after ICO	4.059	1.642	3	4	5
Milestone reached 24 months after ICO	5.326	1.393	5	6	6
Op. development during 6 months after ICO	1.319	1.242	0	1	2
Op. development during 24 months after ICO	2.709	1.775	2	3	4
Crypto Fund (CF) Backing:					
% of startups with CF backing	5.56	22.93	0	0	0
CF Investment Strategy:					
Crypto venture fund, in %	3.05	17.21	0	0	0
Crypto hedge fund, in %	1.71	12.96	0	0	0
Firm Characteristics:					
Expert rating	3.006	0.723	2.500	2.900	3.600
GitHub open-sourced	0.539	0.499	0	1	1
Business model: Platform	0.568	0.495	0	1	1
# targeted industries	3.022	2.432	1	2	4
Ethereum blockchain	0.876	0.330	1	1	1
Offering Characteristics:					
Pre-sale	0.535	0.499	0	1	1
Promotion scheme: Bonus	0.082	0.275	0	0	0
Promotion scheme: Reward	0.310	0.462	0	0	1
KYC	0.457	0.498	0	0	1
# competing ICOs	842	490	515	784	1,051
Market Characteristics:					
Bull market	0.188	0.391	0	0	0
Bear market	0.612	0.487	0	1	1
Sideways market	0.200	0.400	0	0	0
Market volatility during ICO, value-weighted	0.119	0.051	0.088	0.112	0.147
Human Capital Characteristics:					
# team members	11.346	7.191	6	10	15
Team members with technical degree	0.838	0.368	1	1	1
Team members with PhD	0.358	0.479	0	0	1
Team members with crypto experience	0.846	0.361	1	1	1

Note: This table reports summary statistics for operational characteristics, CF backing, and all control variables for our aggregate startup data set. For the statistics on operational variables, the seven milestone steps are numerically encoded from 1 to 7. All variables are defined in Table A1.

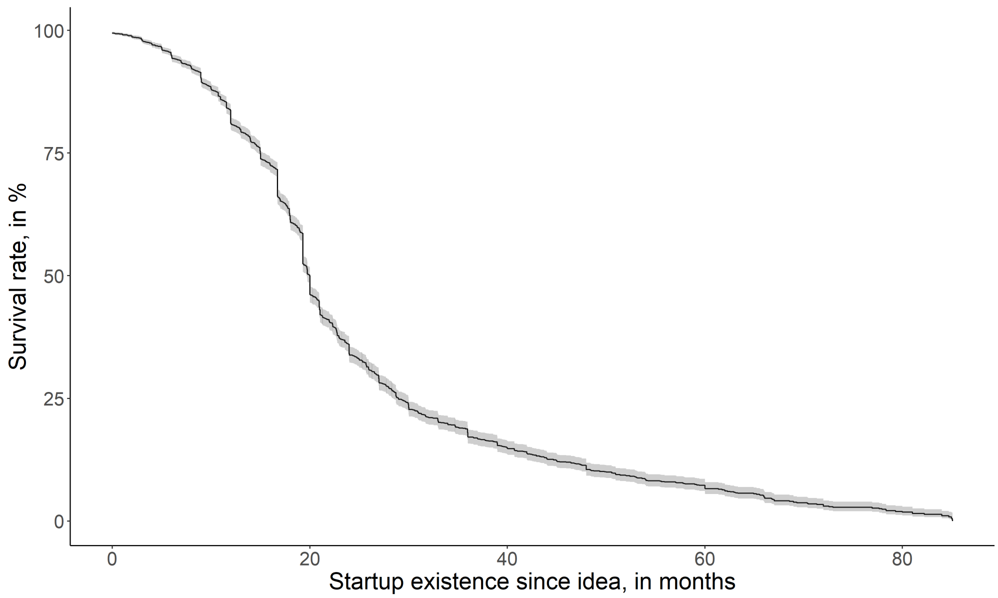
Figure 2: **Duration to Reach Milestones after the Idea**



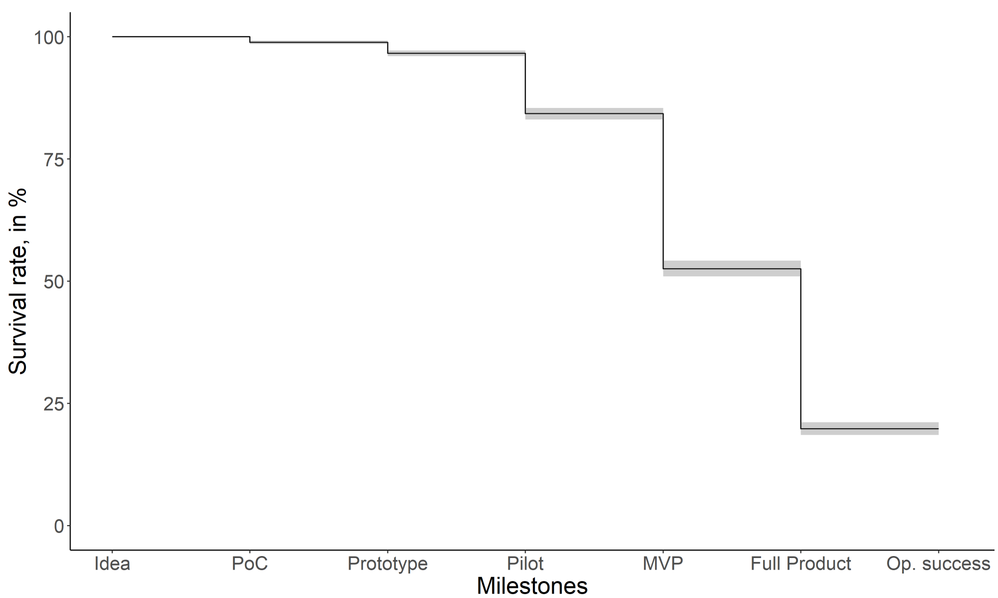
Note: This figure shows the duration, in months, to reach each milestone following idea generation (the first milestone). The lower and upper hinges correspond to the 0.25 and 0.75 quantiles. The lower whisker extends from the lower hinge 1.5x the inter-quartile range (or to the smallest duration, whichever distance is smaller). The upper whisker follows the same logic for the upper range. The box plots are based on milestones with reported dates.

Figure 3: **Startup Milestones: Survival Rate along Startup Life Cycle**

Panel A: Startup Survival over Time



Panel B: Startup Survival along Milestones



Note: This figure shows the Kaplan-Meier survival curves with 95% confidence bands over time (Panel A) and along operating milestones (Panel B). In Panel A, the duration of startup existence is measured from the idea milestone.

Table 4: **Operational Timing of ICO and Financial Performance**

Panel A: Mean Financial Performance along Operational Timing of ICO					
	Funding amount (in $, log)	6-month BHAR (in %)	12-month BHAR (in %)	18-month BHAR (in %)	24-month BHAR (in %)
ICO Following Milestone:					
Ideation	14.92	–30.30	–56.01	–51.91	–54.25
Prototype	15.07	–35.56	–51.98	–57.61	–65.36
Pilot	15.12	–5.84	–44.71	–46.73	–50.73
MVP	14.99	–52.75	–60.62	–70.47	–69.95
Operational success	14.95	–27.85	–60.50	–78.41	–51.61

Panel B: Difference in Selected Means					
	Funding amount (in $, log)	6-month BHAR (in %)	12-month BHAR (in %)	18-month BHAR (in %)	24-month BHAR (in %)
$\triangle$ ***in Means:***					
Pilot – ideation	0.20	24.46	11.30	5.18	3.52
Op. success – pilot	–0.17	–22.01	–15.79	–31.68	–0.88
Op. success – ideation	0.04	2.45	–4.49	–26.50	2.64

Note: This table reports measures for financial performance along the operational timing of ICOs. Panel A displays financial indicators depending on the ICO timing relative to the completion of the operational milestones. Panel B reports the differences in selected means. Due to data availability, the seven milestones have been clustered into five groups: ideation (idea and PoC), prototype, pilot, MVP, and operational success (full product and op. success).

Table 5: **Drivers of Startups' Operational Performance**

	1st stage (Funding)			2nd stage (Excess funding)	
	Startup does not reach		*Funding*	*Startup does not reach*	
Model:	**Frailty**	**Frailty**	**OLS**	**Frailty**	**Frailty**
Dependent variable:	Op. Success	Full Product	Funding (log)	Op. Success	Full Product
	(1)	(2)	(3)	(4)	(5)
Crypto Fund	1.243*	1.424**	0.842***	1.235*	1.407**
	(0.13)	(0.165)	(0.191)	(0.127)	(0.162)
Funding amount, in $ (log)	0.895**	0.864**			
	(0.048)	(0.061)			
Excess funding amount, in $ (log)				0.886**	0.844**
				(0.054)	(0.071)
Firm characteristics:					
Expert rating	0.948	0.967	0.311**	0.926	0.937
	(0.091)	(0.121)	(0.129)	(0.09)	(0.12)
GitHub open-sourced	1.112	1.313**	–0.346**	1.122	1.332**
	(0.101)	(0.138)	(0.146)	(0.101)	(0.138)
Business model: Platform	1.035	0.995	0.013	1.039	1
	(0.095)	(0.127)	(0.138)	(0.095)	(0.127)
# targeted industries	0.976	0.99	–0.016	0.975	0.988
	(0.018)	(0.023)	(0.027)	(0.018)	(0.023)
Ethereum blockchain	0.846	0.735*	–0.072	0.847	0.74*
	(0.141)	(0.174)	(0.208)	(0.141)	(0.174)
Offering characteristics:					
Pre-sale	1.036	1.005	–0.122	1.036	1.013
	(0.093)	(0.124)	(0.134)	(0.093)	(0.124)
Promotion scheme: Bonus	0.579	0.000	0.003	0.571	0.000
	(1.006)	(2967.7)	(0.962)	(1.006)	(2965.3)
Promotion scheme: Reward	1.077	1.124	–0.227	1.077	1.117
	(0.101)	(0.135)	(0.146)	(0.101)	(0.135)
KYC	0.783**	0.779*	0.235	0.787**	0.778*
	(0.105)	(0.14)	(0.158)	(0.105)	(0.14)
# competing ICOs	1.000	1.000	0.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market characteristics:					
Bull market	0.924	0.845	0.177	0.913	0.833
	(0.142)	(0.192)	(0.274)	(0.141)	(0.191)
Bear market	1.25	0.97	0.148	1.269	0.974
	(0.146)	(0.192)	(0.313)	(0.145)	(0.191)
Market volatility during ICO, value-weighted	0.338	0.779	0.507	0.329	0.772
	(0.867)	(1.136)	(1.369)	(0.866)	(1.134)
Human capital characteristics:					
# team members	0.869**	0.836**	0.046***	0.985**	0.984*
	(0.058)	(0.077)	(0.010)	(0.007)	(0.009)
# team members x (excess) funding amount	1.008**	1.011**		1.008*	1.013**
	(0.004)	(0.005)		(0.004)	(0.006)
Team members with technical degree	0.975	0.897	–0.145	0.952	0.867
	(0.132)	(0.169)	(0.193)	(0.131)	(0.169)
Team members with PhD	1.035	1.09	0.154	1.037	1.087
	(0.092)	(0.12)	(0.136)	(0.091)	(0.12)
Team members with crypto experience	1.04	1.088	0.208	1.007	1.054
	(0.154)	(0.205)	(0.219)	(0.153)	(0.204)
Country fixed/random effects	✓	✓	✓	✓	✓
Quarter-year fixed/random effects	✓	✓	✓	✓	✓
Observations	761	739	761	761	739
Log-likelihood	–3358.4	–1890.8		–3360.4	–1890.9
P-value	0.023	0.063		0.036	0.061
McFadden R^2			0.029		

Note: This table reports the frailty model results for the effect of (excess) funding amount (in $, log) and crypto fund backing on operational success. Models 1 and 2 show the baseline models, in which funding amount (in $, log) and a dummy variable for CF backing are the key independent variables. Model 3 shows the "first stage" funding model, in which the funding amount is a function of CF backing and all control variables. Models 4 and 5 are "second stage" models that regress the dependent variables from Models 1 and 2 on CF backing and excess funding, which is defined as the residuals from Model 3. Time-to-liquidation is tested in two ways: (i) a startup does not reach the milestone operational success (Models 1 and 4); and (ii) a startup does not reach the milestone full product (Models 2 and 5). Reported are hazard ratios (exponentiated regression coefficients) and the coefficient standard errors in parentheses. All models include country and quarter-year fixed/random effects. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 6: **Drivers of Startups' Operational Performance: The Impact of Crypto Funds' Investment Strategies**

	1st stage (Funding)			2nd stage (Excess funding)	
	Startup does not reach		*Funding*	*Startup does not reach*	
Model:	**Frailty**	**Frailty**	**OLS**	**Frailty**	**Frailty**
Dependent variable:	Op. Success	Full Product	Funding (log)	Op. Success	Full Product
	(1)	(2)	(3)	(4)	(5)
Venture-style	1.194	1.375	0.698***	1.184	1.349
	(0.177)	(0.225)	(0.257)	(0.175)	(0.222)
Hedge fund-style	1.392*	1.730**	1.056***	1.390*	1.711**
	(0.202)	(0.248)	(0.312)	(0.198)	(0.242)
Funding amount, in $ (log)	0.896**	0.865**			
	(0.048)	(0.061)			
Excess funding amount, in $ (log)				0.887**	0.846**
				(0.053)	(0.071)
Firm controls	✓	✓	✓	✓	✓
Offering controls	✓	✓	✓	✓	✓
Market controls	✓	✓	✓	✓	✓
Human capital controls	✓	✓	✓	✓	✓
Country fixed/random effects	✓	✓	✓	✓	✓
Quarter-year fixed/random effects	✓	✓	✓	✓	✓
Observations	761	739	761	761	739
Log-likelihood	–3358.0	–1888.6		–3360.1	–1890.1
P-value	0.027	0.044		0.044	0.059
McFadden R^2			0.028		

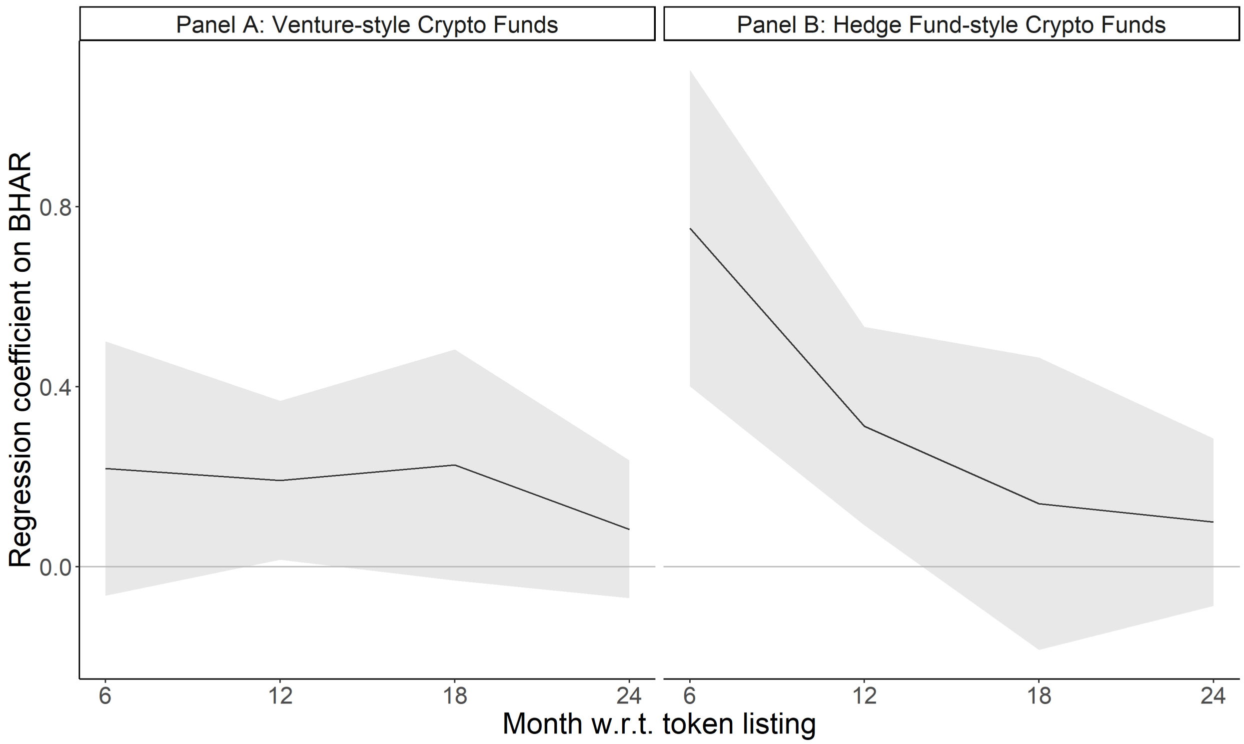
Note: This table tests whether the negative effect of CF backing on operational performance in Table 5 varies by CFs' investment strategy (venture- vs. hedge fund-style). The indicators for operational success are regressed on dummy variables for the two strategies. If at least one crypto hedge fund is invested in one startup, this startup is considered to be hedge fund-style backed. Apart from the split in investment strategies, the dependent variables, models, and reporting logic follow the setup in Table 5. The coefficients of the control variables are suppressed for brevity. All models include country and quarter-year fixed effects. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 7: **Drivers of Startups' Financial Performance: The Impact of Crypto Funds**

	Panel A: Crypto funds			**Panel B: CF investment strategies**		
Dependent variable:	**Funding amount** (1)	**6-month BHAR** (2)	**24-month BHAR** (3)	**Funding amount** (4)	**6-month BHAR** (5)	**24-month BHAR** (6)
Crypto Fund Backing:						
Crypto Fund	0.935***	0.254**	0.070			
	(0.126)	(0.099)	(0.055)			
Venture-style				0.843***	0.218*	0.083
				(0.171)	(0.122)	(0.067)
Hedge fund-style				1.147***	0.752***	0.099
				(0.190)	(0.170)	(0.087)
Operational Characteristics and Timing of ICO:						
Milestone reached at time of ICO	0.055	–0.004	–0.027	0.054	0.007	–0.026
	(0.038)	(0.062)	(0.028)	(0.038)	(0.060)	(0.028)
Milestone reached after 6/24 months		–0.006	0.019		–0.014	0.020
		(0.061)	(0.029)		(0.061)	(0.029)
Strong op. development 6/24 months after ICO		1.014	1.037**		0.924	1.000**
		(0.637)	(0.494)		(0.626)	(0.483)
Milestone after 6/24 months x strong op. dev.		–0.257*	–0.208*		–0.226*	–0.199*
		(0.139)	(0.106)		(0.136)	(0.105)
Firm Characteristics:						
Expert rating	0.386***	0.171**	0.073	0.389***	0.166*	0.069
	(0.106)	(0.087)	(0.056)	(0.106)	(0.085)	(0.056)
GitHub open-sourced	–0.274**	–0.091	0.001	–0.294**	–0.108	–0.002
	(0.116)	(0.087)	(0.052)	(0.117)	(0.085)	(0.052)
Business model: Platform	0.039	–0.068	–0.017	0.043	–0.072	–0.019
	(0.109)	(0.101)	(0.052)	(0.110)	(0.098)	(0.052)
# targeted industries	–0.041	0.0004	–0.008	–0.043	0.002	–0.008
	(0.028)	(0.012)	(0.012)	(0.029)	(0.012)	(0.012)
Ethereum blockchain	0.008	–0.054	–0.075	–0.019	–0.110	–0.082
	(0.180)	(0.130)	(0.074)	(0.183)	(0.129)	(0.073)
Offering Characteristics:						
Funding amount, in $ (log)		0.078	–0.035		0.069	–0.034
		(0.069)	(0.044)		(0.068)	(0.045)
Pre-sale	–0.058	–0.222**	–0.003	–0.056	–0.204**	0.005
	(0.108)	(0.091)	(0.058)	(0.108)	(0.088)	(0.058)
Promotion scheme: Bonus	0.460	0.381	–0.064	0.483	0.552*	–0.073
	(0.462)	(0.281)	(0.136)	(0.473)	(0.313)	(0.131)
Promotion scheme: Reward	–0.220*	0.051	–0.009	–0.218*	0.095	–0.008
	(0.120)	(0.081)	(0.055)	(0.120)	(0.081)	(0.055)
KYC	0.202	–0.073	–0.072	0.207*	–0.055	–0.070
	(0.126)	(0.076)	(0.054)	(0.126)	(0.076)	(0.054)
# competing ICOs	0.0002	–0.0002	–0.0001	0.0002	–0.0001	–0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Market Characteristics:						
Bull market	0.145	0.038	–0.083	0.190	0.059	–0.077
	(0.191)	(0.117)	(0.088)	(0.192)	(0.114)	(0.090)
Bear market	0.214	0.063	–0.0004	0.199	0.014	–0.001
	(0.216)	(0.166)	(0.098)	(0.217)	(0.160)	(0.102)
Market volatility during ICO, value-weighted	1.296	–0.096	1.371**	1.221	–0.163	1.337**
	(1.015)	(0.770)	(0.650)	(1.014)	(0.768)	(0.653)
Human Capital Characteristics:						
# team members	0.035***	0.226***	–0.032	0.035***	0.227***	–0.030
	(0.008)	(0.077)	(0.046)	(0.008)	(0.076)	(0.046)
# team members x funding amount		–0.014***	0.002		–0.014***	0.002
		(0.005)	(0.003)		(0.005)	(0.003)
Team members with technical degree	–0.093	0.241**	0.118	–0.074	0.254**	0.125*
	(0.167)	(0.120)	(0.074)	(0.168)	(0.120)	(0.074)
Team members with PhD	0.117	0.110	0.040	0.114	0.083	0.034
	(0.108)	(0.094)	(0.049)	(0.108)	(0.094)	(0.049)
Team members with crypto experience	0.349	–0.099	0.064	0.354	–0.020	0.073
	(0.224)	(0.135)	(0.159)	(0.225)	(0.139)	(0.160)
Country fixed effects	✓	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓	✓
Observations	978	354	230	978	354	230
Adjusted R^2	0.210	0.338	0.271	0.207	0.363	0.269

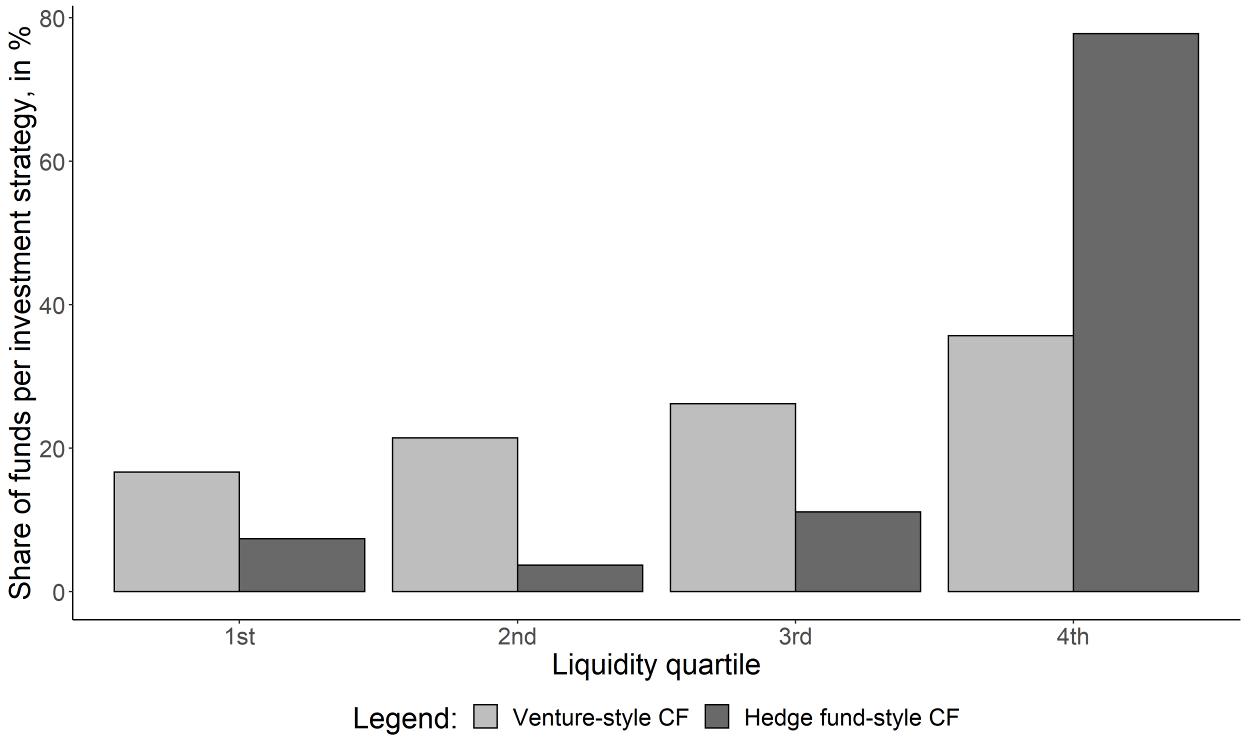
Note: This table reports the regression results for the effect of crypto fund backing on the startup's financial success. Models 1 to 3 measure the CF impact in general; Models 4 to 6 test if the effect of CF backing varies by CFs' investment strategy. Financial success is assessed via the funding amount collected during the ICO (in $, log) and buy-and-hold-abnormal-returns (BHAR) over 6 and 24 months. As controls, the following operational variables are included: (i) The timing of the ICO with regard to the startup's operational milestones. Due to data availability, the seven milestones have been clustered into five groups: ideation (idea and PoC), prototype, pilot, MVP, and operational success (full product and op. success). (ii) The last milestone cluster that has been reached before the end of the respective holding period (e.g., 6 or 24 months). (iii) The speed of the operational development since the ICO, measured by the number of milestone steps a startup has completed since the ICO (and before the end of the respective BHAR period) and encoded with one for top-quartile performers, and zero otherwise. (iv) The interaction between (ii) and (iii). Robust standard errors are reported in parentheses. All models include country and quarter-year fixed effects. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Figure 4: **Drivers of Startups' Financial Performance: The Impact of CF Investment Strategies over Time**



Note: This figure shows the impact of CF investment strategies (venture- vs. hedge fund-style) on startups' token price performance in the secondary market. Panels A and B depict the influence of crypto venture funds and crypto hedge funds, respectively. The funds' regression coefficients (incl. their 95% confidence interval) on BHARs over holding periods from 6 to 24 months are reported in each panel.

Figure 5: **Crypto Hedge Funds Drive Financial Impact via Highly Liquid Tokens**



Note: This figure presents startup backing of CF investment strategies (venture- vs. hedge fund-style) along token liquidity quartiles. Token liquidity, in $ (log), is measured as a token's cumulative trading volume over the 6-month BHAR holding period. Split by investment strategy, the figure shows the share of CFs in each liquidity quartile. For example, about 80% of crypto hedge funds back startups with a token liquidity above the 75th percentile.

Table 8: **Drivers of Startups' Financial Performance: The Impact of ICO Timing**

	Panel A: Crypto funds			Panel B: CF investment strategies		
Dependent variable:	**Funding amount** (1)	**6-month BHAR** (2)	**24-month BHAR** (3)	**Funding amount** (4)	**6-month BHAR** (5)	**24-month BHAR** (6)
Operational Characteristics and Timing of ICO:						
Milestone reached at time of ICO	0.372**	0.425**	–0.056	0.343*	0.360*	–0.064
	(0.177)	(0.207)	(0.113)	(0.178)	(0.205)	(0.111)
(Milestone reached at time of ICO)^2	–0.058*	–0.071**	0.005	–0.053*	–0.059*	0.006
	(0.031)	(0.032)	(0.018)	(0.031)	(0.032)	(0.018)
Milestone reached after 6/24 months		–0.058	0.022		–0.057	0.024
		(0.066)	(0.031)		(0.066)	(0.032)
Strong op. development 6/24 months after ICO		1.266*	1.026**		1.135*	0.984**
		(0.654)	(0.497)		(0.642)	(0.483)
Milestone after 6/24 months x strong op. dev.		–0.295**	–0.208*		–0.259*	–0.199*
		(0.141)	(0.106)		(0.138)	(0.105)
Crypto Fund Backing:						
Crypto Fund	0.925***	0.239**	0.071			
	(0.126)	(0.100)	(0.056)			
Venture-style				0.839***	0.204*	0.086
				(0.172)	(0.119)	(0.068)
Hedge fund-style				1.115***	0.717***	0.101
				(0.190)	(0.173)	(0.087)
Firm characteristics	✓	✓	✓	✓	✓	✓
Offering characteristics	✓	✓	✓	✓	✓	✓
Market characteristics	✓	✓	✓	✓	✓	✓
Human capital characteristics	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓	✓
Observations	978	354	230	978	354	230
Adjusted R^2	0.211	0.345	0.267	0.208	0.367	0.265

Note: This table reports the regression results for the effect of various operational performance indicators and crypto fund backing on the startup's financial success. Models 1 to 3 measure the CF impact in general; Models 4 to 6 test if the effect of CF backing varies by CFs' investment strategy. Financial success is assessed via the funding amount collected during the ICO (in $, log) and buy-and-hold-abnormal-returns (BHAR) over 6 and 24 months. The following operational variables are included: (i) The timing of the ICO with regard to the startup's operational milestones. Due to data availability, the seven milestones have been clustered into five groups: ideation (idea and PoC), prototype, pilot, MVP, and operational success (full product and op. success). (ii) The squared term of (i). (iii) The last milestone cluster that has been reached before the end of the respective holding period (e.g., 6 or 24 months). (iv) The speed of the operational development since the ICO, measured by the number of milestone steps a startup has completed since the ICO (and before the end of the respective BHAR period) and encoded with one for top-quartile performers, and zero otherwise. (v) The interaction between (iii) and (iv). Robust standard errors are reported in parentheses. The coefficients of the control variables are suppressed for brevity. All models include country and quarter-year fixed effects. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 9: **Drivers of Startups' Financial Performance: The Impact of ICO Timing, Split by CF Backing**

	Panel A: Startups w/ CF Backing			Panel B: Startups w/o CF Backing		
Dependent variable:	**Funding amount** (1)	**6-month BHAR** (2)	**24-month BHAR** (3)	**Funding amount** (4)	**6-month BHAR** (5)	**24-month BHAR** (6)
Operational Characteristics and Timing of ICO:						
Milestone reached at time of ICO	–0.096	1.118**	0.289	0.416**	0.211	0.028
	(0.373)	(0.532)	(0.247)	(0.194)	(0.183)	(0.145)
(Milestone reached at time of ICO)^2	0.025	–0.175**	–0.062	–0.066**	–0.045	–0.006
	(0.071)	(0.089)	(0.051)	(0.033)	(0.029)	(0.023)
Milestone reached after 6/24 months		–0.167	0.087		0.004	0.005
		(0.175)	(0.056)		(0.069)	(0.034)
Strong op. development 6/24 months after ICO		–0.011	1.631		1.367*	0.516
		(1.124)	(1.132)		(0.791)	(0.462)
Milestone after 6/24 months x strong op. dev.		0.011	–0.355		–0.326*	–0.091
		(0.283)	(0.246)		(0.172)	(0.100)
Firm characteristics	✓	✓	✓	✓	✓	✓
Offering characteristics	✓	✓	✓	✓	✓	✓
Market characteristics	✓	✓	✓	✓	✓	✓
Human capital characteristics	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓	✓
Observations	124	89	69	854	265	161
Adjusted R^2	0.148	0.107	0.333	0.164	0.412	0.319

Note: This table reports the regression results for the effect of various operational performance indicators on the startup's financial success. Models 1 to 3 measure the impact for the subsample of startups with CF backing, Models 4 to 6 for startups without CF backing. Financial success is assessed via the funding amount collected during the ICO (in \$, log) and buy-and-hold-abnormal-returns (BHAR) over 6 and 24 months. The following operational variables are included: (i) The timing of the ICO with regard to the startup's operational milestones. Due to data availability, the seven milestones have been clustered into five groups: ideation (idea and PoC), prototype, pilot, MVP, and operational success (full product and op. success). (ii) The squared term of (i). (iii) The last milestone cluster that has been reached before the end of the respective holding period (e.g., 6 or 24 months). (iv) The speed of the operational development since the ICO, measured by the number of milestone steps a startup has completed since the ICO (and before the end of the respective BHAR period) and encoded with one for top-quartile performers, and zero otherwise. (v) The interaction between (iii) and (iv). Robust standard errors are reported in parentheses. The coefficients of the control variables are suppressed for brevity. All models include country and quarter-year fixed effects. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Appendix

Table A1: **Variable Definitions and Data Sources**

Variable	Description	Data source
	Panel A: Operational Performance Measurement	
Operational success	Dummy variable equal to one if a startup has reached the milestone operational success, and zero otherwise. We define operational success via a (substantial) expansion in number of users or the realization of first profits.	ICObench
Full product	Dummy variable equal to one if a startup has reached at least the milestone full product, and zero otherwise. We define this milestone via the first full version of the product/service that is released to a broader market.	ICObench
	Panel B: Financial Performance Measurement	
Funding amount	ICO firm valuation measured as the natural logarithm of the total amount raised during the ICO (in $).	ICObench, ICOmarks
Buy-and-hold abnormal return (BHAR)	Calculated by subtracting the market benchmark's buy-and-hold return from a startup's buy-and-hold return over the same holding period after the token listing. We focus on holding periods of 6, 12, 18, and 24 months and primarily use a value-weighted token market index.	CoinMarketCap
	Panel C: Independent Variables: Operational Characteristics	
Milestone reached at time of ICO	The milestone that has been accomplished at the time of the ICO.[6]	ICObench
Milestone reached 6 months after ICO	The milestone that has been achieved until the time of the 6 months token holding period in the secondary market.[6]	ICObench
Milestone reached 24 months after ICO	The milestone that has been achieved until the time of the 24 months token holding period in the secondary market.[6]	ICObench
Op. development during 6 months after ICO	The speed of the operational development since the ICO, measured by the number of milestone steps a startup has completed since the ICO and before the end of the 6-month BHAR period. We define *strong operational development 6 months after ICO* as one for top-quartile performers, and zero otherwise.	ICObench
Op. development during 24 months after ICO	The speed of the operational development since the ICO, measured by the number of milestone steps a startup has completed since the ICO and before the end of the 24-month BHAR period. We define *strong operational development 24 months after ICO* as one for top-quartile performers, and zero otherwise.	ICObench
	Panel D: Independent Variables: Crypto Fund Backing	
Crypto fund (CF)	Dummy variable equal to one if a startup firm has secured CF backing for an ICO, and zero otherwise.	Crypto Fund Research, Crunchbase, investor and startup websites
Crypto venture fund	Dummy variable equal to one if at least one CF that invested during an ICO has a venture-style investment strategy, and zero otherwise.	Crypto Fund Research, investor websites
Crypto hedge fund	Dummy variable equal to one if at least one CF that invested during an ICO has a hedge fund-style investment strategy, and zero otherwise.	Crypto Fund Research, investor websites
	Panel E: Control Variables: Firm Characteristics	
Expert rating	Average of all expert ratings for the ICO. Ratings range from 1 ("low quality") to 5 ("high quality").	ICObench

[6] For statistics and models, the seven milestone steps are numerically encoded from 1 to 7.

GitHub open-sourced	Dummy variable equal to one if the firm makes its source code available on GitHub, and zero otherwise.	GitHub
Business model: Platform	Dummy variable equal to one if the firm plans to create a platform business model, and zero otherwise.	ICObench
# targeted industries	Number of industries the firm serves with its product/offering.	ICObench
Ethereum blockchain	Dummy variable equal to one if the firm builds upon the Ethereum standard, and zero otherwise.	ICObench
	Panel F: Control Variables: Offering Characteristics	
Pre-sale	Dummy variable equal to one if the firm conducted a pre-ICO sale, and zero otherwise.	ICObench, ICOmarks
Promotion scheme: Bonus	Dummy variable equal to one if the firm distributes some tokens for free, and zero otherwise.	ICObench, ICOmarks
Promotion scheme: Reward	Dummy variable equal to one if the firm offers a reward program for its tokens, and zero otherwise.	ICObench, ICOmarks
KYC	Dummy variable equal to one if the firm restricts certain investors, either via a know-your-customer (KYC) process or a white list, and zero otherwise.	ICObench, ICOmarks
# competing ICOs	Number of ICOs that overlap with the period of the initial coin offering of the firm.	ICObench, ICOmarks
	Panel G: Control Variables: Market Characteristics	
Bull market	Dummy variable equal to one if the ICO takes place during the bull market phase (January 2017 until January 2018), and zero otherwise.	ICObench, ICOmarks
Bear market	Dummy variable equal to one if the ICO takes place during the bear market phase (February 2018 until January 2019), and zero otherwise.	ICObench, ICOmarks
Sideways market	Dummy variable equal to one if the ICO takes place during the sideways market phase (February 2019 until September 2020), and zero otherwise.	ICObench, ICOmarks
Market volatility during ICO	Change in returns of the value-weighted token market benchmark during the period of the ICO.	ICObench, ICOmarks
	Panel H: Control Variables: Human Capital Characteristics	
# team members	Number of team members of the firm.	ICObench
Team members with technical degree	Dummy variable equal to one if a team includes at least one member with a college degree in a technical field, and zero otherwise.	LinkedIn
Team members with PhD	Dummy variable equal to one if a team includes at least one member with a PhD degree, and zero otherwise.	LinkedIn
Team members with crypto experience	Dummy variable equal to one if a team includes at least one member with prior experience in blockchain technology, and zero otherwise.	LinkedIn

Table A2: **Pairwise Correlations**

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
Operational Performance:																
1. Reached operational success																
2. Reached at least full product	0.48															
Financial Performance:																
3. Funding amount	0.05	0.03														
4. 6-month BHAR	-0.01	-0.02	0.002													
5. 12-month BHAR	0.06	0.002	-0.004	0.49												
6. 18-month BHAR	-0.01	-0.06	-0.01	0.48	0.76											
7. 24-month BHAR	0.01	-0.05	0.05	0.39	0.69	0.76										
Operational Characteristics:																
8. Milestone reached at time of ICO	0.10	0.16	0.02	-0.06	-0.01	-0.01	-0.06									
9. Milestone reached 6 months after ICO	0.16	0.29	0.08	-0.07	-0.07	-0.08	-0.11	0.71								
10. Milestone reached 24 months after ICO	0.52	0.74	0.03	-0.05	-0.07	-0.01	0.03	0.25	0.51							
11. Op. development during 6 months after ICO	0.10	0.22	0.001	-0.08	-0.09	-0.08	-0.05	-0.36	0.39	0.40						
12. Op. development during 24 months after ICO	0.35	0.49	-0.09	-0.004	-0.01	0.06	0.03	-0.65	-0.19	0.57	0.52					
Crypto Fund (CF) Backing:																
13. Crypto Fund	-0.04	-0.06	0.25	0.18	0.13	0.12	0.04	-0.01	-0.04	0.01	-0.03	0.02				
14. Crypto venture fund	-0.02	-0.05	0.17	0.15	0.11	0.10	0.03	0.004	0.02	0.03	0.01	0.03	0.73			
15. Crypto hedge fund	-0.03	-0.04	0.16	0.11	0.06	0.04	0.02	-0.01	-0.04	-0.07	-0.04	-0.04	0.54	-0.02		
Firm Characteristics:																
16. Expert rating	0.05	-0.01	0.16	-0.07	0.05	0.02	-0.01	0.06	0.08	0.05	0.04	0.04	0.09	0.06	0.06	
17. GitHub open-sourced	-0.03	-0.02	0.005	-0.08	0.04	0.05	-0.02	0.02	0.01	-0.11	0.03	-0.02	0.06	0.05	0.04	0.45
18. Business model: Platform	-0.03	-0.002	0.05	0.02	0.01	-0.02	0.07	0.01	0.08	0.05	0.02	0.02	0.03	0.03	0.01	0.13
19. # targeted industries	0.01	0.01	-0.03	-0.07	-0.03	-0.06	-0.03	0.04	0.04	0.09	0.02	0.11	-0.04	-0.02	-0.02	0.24
20. Ethereum blockchain	0.002	0.01	0.03	-0.02	-0.05	-0.07	-0.01	0.03	0.01	-0.01	-0.04	-0.07	0.01	-0.02	0.03	0.02
Offering Characteristics:																
21. Pre-sale	0.04	0.04	-0.03	-0.10	-0.07	-0.11	-0.12	0.05	-0.01	0.04	0.01	0.01	-0.06	-0.06	-0.03	0.29
22. Promotion scheme: Bonus	0.01	0.02	0.002	-0.06	0.09	-0.07	-0.06	-0.04	-0.03	0.08	0.07	0.12	-0.04	-0.03	-0.02	0.08
23. Promotion scheme: Reward	0.001	0.01	-0.07	-0.05	-0.04	-0.10	-0.08	0.08	0.07	0.09	0.01	0.08	-0.06	-0.04	-0.04	0.30
24. KYC	0.04	0.005	0.03	-0.09	-0.07	-0.17	-0.09	0.11	0.10	0.10	-0.03	0.05	-0.003	0.01	-0.005	0.41
25. # competing ICOs	0.02	0.03	-0.02	-0.16	-0.16	-0.27	-0.18	-0.08	0.06	0.05	0.22	0.07	-0.07	-0.08	-0.04	0.05
Market Characteristics:																
26. Bull market	-0.004	-0.01	0.09	0.10	0.13	0.21	0.16	-0.09	-0.03	-0.07	0.02	-0.06	0.10	0.06	0.03	-0.19
27. Bear market	0.02	0.08	0.05	-0.12	-0.12	-0.23	-0.17	-0.06	-0.01	0.07	0.06	0.05	-0.01	-0.01	0.01	0.15
27. Sideways market	0.01	-0.05	-0.14	0.06	-0.03	-0.02		0.14	0.07		-0.11		-0.08	-0.06	-0.04	0.16
29. Market volatility during ICO, value-weighted	0.01	0.04	0.12	-0.10	0.05	0.05	0.05	-0.07	0.06	0.09	0.10	-0.05	-0.02	-0.01	-0.03	-0.13
Human Capital Characteristics:																
30. # team members	0.03	0.01	0.19	-0.04	-0.08	0.01	-0.03	0.09	0.10	0.04	0.01	0.05	0.08	0.06	0.05	0.40
31. Team members with technical degree	-0.02	-0.01	0.11	-0.07	0.03	-0.005	0.001	0.07	-0.01	-0.03	-0.09	-0.04	0.08	0.07	0.02	0.16
32. Team members with PhD	0.01	-0.02	0.15	0.05	0.03	0.02	0.07	0.06	0.02	0.04	-0.04	0.02	0.09	0.06	0.08	0.19
33. Team members with crypto experience	0.01	-0.01	0.14	0.01	-0.13	-0.09	-0.03	0.03	0.02	0.04	-0.02	-0.06	0.07	0.05	0.03	0.26

Table A2 (continued): **Pairwise Correlations**

	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.	33.
Operational Performance:																	
1. Reached operational success																	
2. Reached at least full product																	
Financial Performance:																	
3. Funding amount																	
4. 6-month BHAR																	
5. 12-month BHAR																	
6. 18-month BHAR																	
7. 24-month BHAR																	
Operational Characteristics:																	
8. Milestone reached at time of ICO																	
9. Milestone reached 6 months after ICO																	
10. Milestone reached 24 months after ICO																	
11. Op. development during 6 months after ICO																	
12. Op. development during 24 months after ICO																	
Crypto Fund (CF) Backing:																	
13. Crypto Fund																	
14. Crypto venture fund																	
15. Crypto hedge fund																	
Firm Characteristics:																	
16. Expert rating																	
17. GitHub open-sourced																	
18. Business model: Platform	0.09																
19. # targeted industries	0.18	0.34															
20. Ethereum blockchain	0.01	0.05	-0.03														
Offering Characteristics:																	
21. Pre-sale	0.15	0.09	0.18	-0.01													
22. Promotion scheme: Bonus	0.03	0.04	0.06	-0.01	0.04												
23. Promotion scheme: Reward	0.18	0.06	0.16	-0.002	0.16	0.11											
24. KYC	0.18	0.06	0.23	-0.03	0.17	0.09	0.26										
25. # competing ICOs	0.06	-0.04	0.07	0.02	0.03	0.01	0.12	0.11									
Market Characteristics:																	
26. Bull market	-0.07	-0.02	-0.15	0.01	-0.13	-0.10	-0.28	-0.37	-0.23								
27. Bear market	0.09	-0.03	0.12	0.01	0.14	-0.05	0.17	0.21	0.57	-0.33							
27. Sideways market	0.05	0.03	0.06	-0.05	0.09	-0.08	0.08	0.14	-0.18	-0.23	-0.33						
29. Market volatility during ICO, value-weighted	-0.04	-0.02	-0.06	0.02	-0.06	-0.01	-0.14	-0.18	0.09	0.33	0.13	-0.31					
Human Capital Characteristics:																	
30. # team members	0.20	0.09	0.14	0.03	0.13	0.06	0.14	0.28	0.03	-0.11	0.10	-0.001	-0.03				
31. Team members with technical degree	0.10	0.03	0.05	0.04	0.02	0.04	0.04	0.15	0.06	-0.05	0.12	-0.12	0.01	0.30			
32. Team members with PhD	0.09	0.06	0.09	0.03	0.03	0.05	0.04	0.16	0.02	-0.05	0.06	-0.06	-0.02	0.35	0.22		
33. Team members with crypto experience	0.08	0.06	0.05	0.01	0.02	0.03	0.05	0.19	-0.03	-0.04	0.01	0.02	-0.04	0.34	0.27	0.18	