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Decentralized Finance, Crypto Funds, and Value Creation in Tokenized Firms*

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Abstract

Crypto funds (CFs) represent a novel investor type in entrepreneurial finance. CFs intermediate Decentralized Finance (DeFi) markets by pooling contributions from crowd-investors and investing in tokenized startups, combining venture- and hedge-style investment strategies. We compile a unique dataset combining token-based crowdfunding (Initial Coin Offering, ICO) data with proprietary performance data of CFs. CF-backed startup ventures obtain higher ICO valuations, outperform their peers in the long run, and benefit from token price appreciation around CF investment disclosure in the secondary market. Moreover, CFs themselves beat the market by roughly 2.5% per month. Outperformance is persistent, indicating that CFs generate returns because of their skills, rather than luck. The performance effects for CFs and CF-backed startups are driven by a fund's investor network centrality.

Keywords: Crypto Funds (CFs), Initial Coin Offering (ICO), Decentralized Finance (DeFi), Blockchain-based Crowdfunding, Entrepreneurial Finance
JEL Codes: G24, G32, K22, L26

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1 Introduction

Decentralized Finance (DeFi) builds on blockchain technology to disintermediate, inter alia, entrepreneurial financial markets (Chen and Bellavitis, 2020). Disintermediation in entrepreneurial finance started with equity-based crowdfunding platforms (Ahlers et al., 2015; Belleflamme et al., 2014; Mollick, 2014). Its main promise is that there is no need to remunerate an intermediary such that entrepreneurs and investors can enjoy the transaction surplus exclusively.[1] DeFi markets for startups further economize on transaction costs by replacing crowdfunding platforms with smart contracts.[2] Smart contracts refer to computer protocols stored in a blockchain or some other type of distributed ledger that automatically execute the exchange of investors' pecuniary contributions to venture projects with entrepreneurs' tokens, which represent claims on future products or services. Token-based crowdfunding, also known as Initial Coin Offerings (ICOs) or token sales (Adhami et al., 2018; Bellavitis et al., 2020; Bellavitis et al., 2021; Colombo et al., 2021; Fisch, 2019; Howell et al., 2020; Lyandres et al., 2022; Momtaz, 2020), rely on smart contracts to minimize the degree of intermediation in entrepreneurial financial markets.

However, a novel type of intermediary, so-called crypto funds (CFs), has appeared on stage in entrepreneurial finance (Mokhtarian and Lindgren, 2018; Momtaz, 2022; Zetzsche et al., 2020), suggesting that DeFi markets for startups are characterized by an *increasing* degree of intermediation. As Figure 1 illustrates, the number of newly established CFs per year goes hand in hand with the evolution of the overall ICO market. According to Crypto Fund Research (2021), total assets under management in CFs globally climbed from $8.3 billion in mid-2018 to $57.5 billion at the end of 2021.[3] Our paper is the first to empirically analyze the seemingly paradoxical emergence and role of CFs as intermediaries in entrepreneurial finance.

[Place Figure 1 about here.]

Asymmetric information and agency problems often prevent the socially optimal allocation of financial capital to entrepreneurs (Block et al., 2018; Hall and Lerner, 2010). Specialized intermediaries reduce these frictions and improve the efficiency of entrepreneurial financial markets through information production and certification services (Hsu, 2004) as

[1] Venture Capital (VC) funds typically charge 20% in performance and 2% in annual management fees. Crowdfunding platforms are also charging fees, often in the amount of 7%, which is commensurate to the underwriting fees in initial public offerings (IPOs).

[2] Momtaz (2022) notes that the average transaction fee to execute a smart contract on the Ethereum blockchain was less than $2 in January 2022.

[3] A large fraction of CFs is domiciled in the British Virgin Islands or the Cayman Islands for tax, legal, or other regulatory reasons, although half of them hold primary U.S. offices.

well as delegated monitoring and operational guidance (Bertoni et al., 2011; Colombo and Grilli, 2010). Provided that CFs are capable to alleviate crypto market frictions and reduce participation costs for investors (Allen and Santomero, 1998), they can help to improve the efficiency of DeFi markets for startups.

The only existing empirical study on crypto funds is Fisch and Momtaz (2020).[4] They regress the token price performance after crypto-exchange listing on a dummy for CF backing and find a positive effect. Our study expands on their work by employing a novel, proprietary dataset to offer an extensive analysis of how CFs impact the success of tokenized startups along various dimensions. We also examine whether CFs are able to outperform individual DeFi investors. In essence, we fill the void in the entrepreneurial finance literature on the role of DeFi intermediaries in token-based crowdfunding markets by posing the following research question:

How do crypto funds impact the success of tokenized startups, and are crypto funds themselves able to "beat the market" of crowd-investors?

Thanks to the liquidity provided by token exchange platforms, stakes in tokenized startups are now not only traded in *primary* markets but also in *secondary* token markets. This institutional setup allows us to gain new insights into entrepreneurial finance, e.g., how CF investments in startups impact their short- and long-term performance. Moreover, CFs are interesting in their own right because they combine venture-style investment strategies in startups with hedge fund-like trading strategies in liquid secondary token markets.

Our main premise is that CFs generate value in DeFi markets for startups, which allows us to derive three overarching testable hypotheses. The first, the *Startup Firm Outperformance Hypothesis* (*SFOH*), posits that CF-backed startup firms are more successful than their non-CF-backed peers in primary and secondary markets for tokens. We expect that CF-backed startups achieve higher valuations during an ICO, deliver higher buy-and-hold abnormal returns after a token exchange listing, and experience abnormal token price appreciations associated with CFs' investment announcements in the secondary market. The rationale for the *SFOH* is that CFs mitigate the severe information asymmetry problems in ICOs and extract informational rents. On the one hand, their superior screening skills lead to a selection effect. CFs are able to pick tokenized startups with better success prospects than crowd-investors (Bertoni et al., 2011; Colombo and Grilli, 2010; Fisch and Momtaz, 2020). CF backing itself may thus signal project quality and legitimacy to crowd-investors (Hsu, 2004). On the other hand, there is a treatment effect from CFs' active role in monitoring and advising (Cumming et al., 2017; Gompers, 1995; Hellmann and Puri, 2002;

[4]Momtaz (2022) also examines crypto funds, but his focus is on aggregate market efficiency, not on the impact of CFs on tokenized startups.

Puri and Zarutskie, 2012). This latter treatment effect of CF involvement is at the center of our empirical analysis.

The second hypothesis, the *Crypto Fund Outperformance Hypothesis* (*CFOH*), submits that CFs are able to beat the aggregate market of crowd-investors, and that this outperformance is persistent over time, i.e., it is driven by skill rather than luck. CFs should be able to outperform crowd-investors because their incentive to develop specialized human capital exceeds that of individual investors (Fisch and Momtaz, 2020). We also provide several arguments for CF outperformance and persistence that builds on complementary evidence in the mutual fund and hedge fund literature.

Finally, the third hypothesis, the *Investor Network Hypothesis* (*INH*), posits that the positive performance effects conjectured by the *SFOH* and the *CFOH* increase in CFs' network centrality. More central CFs have better access to information and investment opportunities, they can influence the dynamics of information dissemination, and are better able to 'open doors' for their backed startups (Bajo et al., 2020). Moreover, CFs' network centrality may be associated with influence, prominence, and prestige (Davis and Robbins, 2005), which could serve as an important signal to crowd-investors.

The empirical results confirm our hypotheses. First, tokenized startups benefit from CF backing both in terms of their valuation during token-based crowdfunding campaigns and their subsequent token price performance in the secondary market. Using different estimation approaches, we find evidence for a treatment effect. Rather that simply selecting ICO startups that would achieve superior performance irrespective of their involvement, CFs have the ability to enhance performance through their role as active monitors and strategic advisers. We further measure announcement-related abnormal returns of tokenized startups when CF investments are disclosed in the secondary market. Event-study evidence shows that crowd-investors welcome CF investments, i.e., the token price reactions are significantly positive. Collectively, our evidence lends support to the *SFOH* that CF-backed, tokenized startups outperform in the primary and secondary markets for tokens.

Second, the average CF outperforms the token market by roughly 2.5% per month. CF outperformance is even persistent, suggesting that CFs outperform crowd-investors because of skill rather than luck. These findings, confirming the *CFOH*, are intriguing not only because token markets have been praised for democratizing access to finance (Bollaert et al., 2021; Fisch et al., 2022), but also because traditional mutual funds underperform the market net-of-fees (Fama and French, 2010). Our results suggest that CFs persistently outperform the market. The optimal strategy for crowd-investors is to invest in CFs, which in turn leads to a re-centralization of entrepreneurial finance and counteracts entrepreneurs' pursuit to disintermediate markets with the help of blockchain technology.

Finally, we show that an important driver that causes the outperformance of CF-backed startups as well as CFs themselves is the investor network. We measure the centrality of a fund in the network of all CFs in the sample by counting the number of investment ties with other CFs. Corroborating our *INH*, outperformance on both startup and CF level is increasing in a CF's investor network centrality.

The rest of the paper is structured as follows. Section 2 describes the institutional background and derives testable hypotheses. Section 3 provides details on our data collection process and the econometric approach. Section 4 presents our empirical results. Finally, Section 5 discusses our contribution to the literature, highlights limitations, and shows potential avenues for future research.

2 Background and Hypotheses

2.1 Institutional Background

2.1.1 Token-Based Crowdfunding

In a token offering, or initial coin offering (ICO), startups raise capital by selling tokens to investors (Fisch, 2019; Momtaz, 2020). 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 represent the most frequently issued token type in ICOs (Bellavitis et al., 2020; Momtaz, 2020).[5] During an ICO, investors can buy tokens at a pre-defined price from the issuer. After the ICO, tokens can be either exchanged among investors or converted into other cryptocurrencies (or fiat currencies) on liquid cryptocurrency exchanges.[6]

ICOs represent an innovative entrepreneurial finance mechanism, which has evolved from crowdfunding by using blockchain technology to issue and trade, on an organized market, stakes in startups (Belitski and Boreiko, 2021; Fisch, 2019; Howell et al., 2020; Li 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 peer-to-peer startup financing transactions,

[5]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 initiated a gradual shift from utility to security token offerings (Lambert et al., 2021).

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

which rely on smart contracts to automate "trustless" transactions between entrepreneurs and investors (Amsden and Schweizer, 2018; Fisch et al., 2022; Momtaz, 2022).

From an issuing firm's perspective, ICOs have several benefits (Ofir and Sadeh, 2021). First, startups can raise capital from investors without diluting their holdings. Second, the ICO mechanism allows outreach to a global investor base at almost no transaction costs. Third, issuers automatically create users for their products or services, who should be more engaged in the project. Fourth, investors join the platform not only to enjoy its utility, but also to benefit from rising token price as a result of growing network size (Benedetti and Nikbakht, 2021; Cong et al., 2021). ICO investors benefit also from their ability to easily sell holdings in the early stages of the firm (Lyandres et al., 2022).

2.1.2 Crypto Funds

A CF is a portfolio containing of liquid, public digital tokens managed by one single manager or a team of individuals. As intermediaries in entrepreneurial finance, CFs exploit the fact that tokenized startups can be traded in public secondary markets. Fund investors can buy into these funds so that they share in the profits as the value of the fund grows.

Crypto assets are an interesting asset class for fund managers because they differ from traditional funds in several ways. First, CFs mostly trade in non-securities, avoiding much of the regulation imposed on traditional funds. Trading in non-securities largely exempts them from the *Investment Company Act*, enabling them to cater to small private investors, who are not accredited or qualified in the legal sense (Mokhtarian and Lindgren, 2018).[7] Moreover, crypto funds are largely exempted from the *Advisers Act*. This raises limits on performance fees that can be charged to small investors, thus making CFs more financially attractive. Second, blockchain technology saves CFs time and fees that would otherwise incur for third-party custodians pursuant to the *Advisers Act*. Third, with some exceptions, tokens are taxable only in the case of 'recognition events,' i.e., if they are exchanged for fiat money. This allows fund investors to optimize the timing and the amount of their personal tax liabilities (Mokhtarian and Lindgren, 2018). Finally, the liquidity of tokens lifts funds' burden to identify and invest in 'unicorns' to compensate for the large number of failed projects because liquid markets allow CFs to exit at any time (Kastelein, 2017).

Tokens as an asset class still lack legitimacy in the broader financial community, preventing direct investments from institutional investors. Entry barriers relate to legal and regulatory uncertainty, lack of corporate-ready infrastructure, low quality market data, and insufficient knowledge about the technical underpinnings of the token market. Specialized

[7]Indeed, CFs attract small investors with significantly lower minimum investment requirements. According to Crypto Fund Research (2021), the median minimum fund investment amounts to $100,000.

intermediaries such as CFs can act as spear-heads in this market and legitimate tokens for other institutional investors.

2.1.3 Crypto Fund Strategies

According to Crypto Fund Research (2021), there were more than 850 active CFs worldwide in mid-2021. Most CFs act as either venture-style or hedge-style funds. Only a small number of CFs are index funds, mostly passive or tracker funds.

Crypto venture funds make equity-type investments. Investors pool their money to buy into new ventures and altcoins, benefitting from diversification in dispersed investments. Venture capital funds not only have competence in gauging project quality and probability of success, but they also take an active role in the firms they finance (Da Rin et al., 2013). Similarly, at least in utility token projects, crypto venture funds provide both value-adding services and control actions. Once the assets have grown by a sufficient amount, they are sold-off and investors capture their profits.

Crypto hedge funds invest and actively trade in tokens. Compared to traditional hedge funds (Fung and Hsieh, 2013), the range of trading strategies available for crypto hedge funds is still limited. However, crypto hedge funds can take advantage of mispricing and arbitrage opportunities in many ways. For example, Liu and Tsyvinski (2021) show a strong time-series momentum effect in token returns, and proxies for investor attention strongly predict future token returns.[8] While Liu and Tsyvinski (2021) conclude that fundamental-to-market valuation ratios, e.g., the number of used adoptions over market capitalization, are unrelated to token returns, Cong et al. (2021) find they negatively predict future returns. Makarov and Schoar (2020) document that cryptocurrency markets exhibit periods of potential arbitrage opportunities across exchanges. Griffin and Shams (2020) show that Bitcoin prices can be gamed and manipulated.[9]

[8]In contrast, in their theoretical paper, Schilling and Uhlig (2019) argue that the evolution of token returns should follow a martingale, and thus returns are not predictable.

[9]The most common fund strategies are quantitative, discretionary long/short, discretionary long-only, and multi-strategy (PwC, 2021). Crypto hedge funds with a quantitative approach to the market (directional or market-neutral) implement strategies such as market making, arbitrage, and low latency (algorithmic) trading. Discretionary long/short funds cover a broad range of strategies including long/short, relative value, event driven, technical analysis and some strategies that are crypto-specific, such as mining. Discretionary long only funds invest in early-stage token/coin projects and have a longer time horizon, thus requiring the longest lock-up periods and strictest gate provisions of all strategies. These strategies often require trading derivatives (e.g., Bitcoin futures or options) and taking short positions.

2.2 Conceptual Framework

2.2.1 Eliminating the Need for Financial Intermediation

Traditional market-based finance depends on a range of intermediaries that bring together disparate market participants. While there is no scope for financial intermediaries to improve welfare in perfect and complete markets (Fama, 1980), frictions such as transaction costs and information asymmetry are essential for understanding the need for intermediation (Allen and Santomero, 1998; Bhattacharya and Thakor, 1993). Financial intermediaries signal their informed status by investing their wealth in assets about which they have special knowledge (Leland and Pyle, 1977) and overcome asymmetric information as 'delegated monitors' (Diamond, 1984). Intermediaries also reduce transaction costs by connecting market participants and building trust (Shiller, 2012).

Because many financial intermediaries are large, there is a tension between the need for efficient transactions and the ability of intermediaries to maximize their self-interests, raising concerns over monopoly power (Cohen, 2019). Philippon (2016, 2019) finds that the average costs of financial intermediation in the U.S. has held steadily at around 2% of transaction amounts. Although sophisticated technology and globalization together have already characterized financial markets for many years, these improvements in information techniques have not been passed on as lower costs to the end users of financial services.

DeFi entails radical changes, embracing financial technology, cryptrcurrencies, and digital assets as the most disruptive evolution in modern finance (Zetzsche et al., 2020). It eliminates the need for intermediaries by creating a solely code-based, openly accessible, and transparent financial system.[10] A *decentralized* provision of financial services increases the share of the transaction surplus that transaction parties can enjoy exclusively, reduces transaction costs, and creates network effects that facilitate superior screening technology without incurring monopoly costs (Allen et al., 2021; Chen and Bellavitis, 2020).[11]

Decentralized fundraising through ICOs for early-stage ventures is one important new business model that has only become viable through blockchain technology (Bellavitis et al., 2021; Chen and Bellavitis, 2020; Momtaz, 2020). While traditional venture fundraising involves large frictions, because many investors only trust and invest in projects with

[10]From a more technical perspective, Meyer et al. (2021) summarize that DeFi refers to finance protocols 1) built with *smart contracts* (agreements that are programmatically enforced without human intervention), 2) which are *trustless* (all transactions are based on 'distributed trust' without pre-existing trusted relationships, validated through distributed consensus and protected through advanced cryptography), and 3) developed on *permissionless, public blockchains* (decentralized open networks available to everyone to participate in the consensus process that blockchains use to validate transactions and data).

[11]Existing studies discuss these implications of DeFi mostly for bank lending intermediation (Boot et al., 2021; Frost et al., 2020; Stulz, 2019). These studies also express a warning that DeFi could entail negative welfare effects due to market power that arises from network externalities and portfolio effects.

strong network ties (Hallen, 2008; Hallen and Eisenhardt, 2012), utility tokens allow startups to raise funds for a new project in a trustless way from previously unknown investors. Furthermore, token trading platforms reduce valuation discounts due to illiquidity (Barg et al., 2021) and enable investors to exit.

DeFi's proliferation should have coincided with a *reduction* in intermediation, and thus the increasing emergence of CFs as players in a *decentralized* ICO market for startups seems puzzling. There are two plausible explanations for increasing CF intermediation: 1) high participation costs in the crypto market, and 2) new types of DeFi-specific risks.

2.2.2 Participation Costs

Traditional frictionless theories where financial intermediaries do not add economic value assume that all investors are involved and there is full participation in markets. Participation in ICO markets is strongly limited, which can be explained in terms of participation costs. The value of people's time, particularly many professionals, has increased substantially (Allen and Santomero, 1998). CFs have relatively low participation costs and thus are an efficient method to invest for investors whose direct costs of participation have risen. For example, there are sizeable fixed costs of learning about token markets. Fixed costs include an understanding of the distribution of token returns and how to monitor changes over time.[12] In addition, monitoring crypto markets on a day to day basis causes substantial marginal costs. Investors need to understand how the expected distribution of token payoffs is changing and how portfolios must be adjusted.[13]

Financial intermediaries also provide an important risk transformation function (Allen and Santomero, 1998). As informed and skilled intermediaries, CFs are able to achieve better diversification and create token portfolios with higher risk-adjusted returns. These superior distributional characteristics allow investors to monitor their portfolios on a less frequent basis. As a result, through risk transformation, CFs reduce the participation costs of revising portfolios over time.

The specific types of risk that are inherent in the market for token-based crowdfunding drive up the initial (fixed) participation costs even further. First, there is high investment risk. ICOs typically occur in a very early stage of a venture's life cycle with unknown project quality and outcome, and utility tokens do not have any counter value or real-world usage at the time of the ICO (Fisch, 2019). Moreover, tokens do not lead to any legal entitlement

[12] Brennan's (1975) model shows that fixed setup costs of this kind have the effect of reducing the optimal number of assets to include in an investor's portfolio, thus resulting in low levels of diversification.

[13] Standard portfolio theory dictates that investors have to constantly review and alter their portfolios as new information arrives at the market that changes the distribution of asset returns (Merton, 1971).

because there is high potential for malignant behavior and outright fraud in ICOs (Hornuf et al., 2022; Howell et al., 2020; Momtaz, 2021b; SEC, 2017).

Second, the amount of information available in ICOs is low due to the absence of formal disclosure requirements. There is large heterogeneity in amount and type of information available, and ventures typically publish white papers that tend to be poor and misleading (Cohney et al., 2019). Sometimes the most basic pieces of information, such as venture history, biographies of founders, or financial predictions, are not available (Colombo et al., 2021; Fisch, 2019; Momtaz, 2021a; Zetzsche et al., 2019), and moral hazard problems create limits to signaling even from high-quality issuers (Momtaz, 2021b),

Third, while blockchain technology was developed out of a preference for anonymity, this imposes an inherent dilemma. Many investors demand anonymity to trade, conflicting with the reduction of information asymmetry necessary to ensure the functioning of the market. Exacerbating the problem further, smart contracts limit the amount of tokens that can be issued. An issuer can tap the market only once and thus has moral hazard motives to exaggerate the information disclosed to maximize the funding amount (Momtaz, 2021b).

2.2.3 DeFi-Specific Risks

The reliance on blockchain technology requires a great deal of technological knowledge to assess the quality of the project. (Bellavitis et al., 2021; Fisch, 2019; Ofir and Sadeh, 2021). ICO investors must have technical expertise and at least the willingness to familiarize themselves with the technical background and application proposed by each venture, which create novel types of DeFi-specific risks. These risks require skills beyond those in the traditional fund industry, giving further rise to a business case for specialized CFs. While individual investors are not able to acquire sufficient technical expertise, CFs use specialized teams of blockchain technology-savvy and financial experts. The relevant risks broadly refer to (1) protocol-interface risks, (2) protocol-immanent risks, (3) smart-contract risks, (4) oracle risks, and (5) governance-related risks (Harvey et al., 2021).

At the protocol-interface to the external environment, interconnectedness with traditional finance poses risks. First, stablecoins are backed by reserves parked at banks, thus being dependent on these banks. Second, there are just a few banks (e.g., Silvergate Bank) who dominate crypto interfaces, and make the whole DeFi system vulnerable, as they centralize DeFi at its interfaces. Third, several large DeFi players (e.g., Coinbase or Binance) now offer retail and/or consumer DeFi apps, whereby they are able to amass large fund pools, which centralizes DeFi at its retail interface (Zetzsche et al., 2020).

At the protocol-immanent level, there are operational and technical risks, often associated with the potential extraction of private benefits of control by validators and miners.

These come in the form of human politics (e.g., the *ETH* hard fork as a reaction to the *Parity* wallet hack), consensus failures (e.g., 51% attacks on proof-of-work blockchains), miner extracted value (Daian et al., 2020)[14], or validator cartels around proof-of-stake blockchains (e.g., Justin Sun and the STEEM network; Carter and Jeng, 2021).

Smart contracts may have technical vulnerabilities as most are not backed by third parties, resulting in irrevocable losses of funds if the smart contracts are faulty, they are difficult to update once deployed, and may be subject to contract-specific risks such as reentrancy risks, transaction sandwiches, and logical bugs (Werner et al., 2021). Oracle attacks by which attackers manipulate the information (e.g., underlying prices of derivatives) that so-called oracles feed into DeFi applications such as automated market maker exchanges are an important threat to the entire DeFi ecosystem. Relatedly, flash loans may allow for intra-contract arbitrage (Wang et al., 2021). Finally, governance-related risks include simple risks such as key loss, insider theft, outsider theft, and regulatory pressure. Governance token holders may act as activist investors and change development decisions, potentially impairing the trust put into consensus protocols. "Pseudo-equities" (i.e., tokens with unclear regulatory status) may also face more regulatory scrutiny in the future, should they be deemed as "unregistered securities" with potentially far-ranging consequences for both issuers and token holders.

2.3 Overarching Hypotheses

2.3.1 Startups and Involvement of Crypto Funds

Our first hypothesis, the *Startup Firm Outperformance Hypothesis* (*SFOH*), pertains to how startup firms backed by CFs perform relative to their non-CF-backed peers in primary and secondary token-based crowdfunding markets.[15] Its main premise is that CFs are sophisticated investors. They have a better understanding of a firm's quality and are better able to mitigate information asymmetry frictions than retail investors (Chemmanur et al., 2009; Demiralp et al., 2011; Lee and Wahal, 2004; Schenone, 2010). These skills of institutions are attributable to screening and treatment (Bertoni et al., 2011; Brav and Gompers, 1997; Colombo and Grilli, 2010; Gompers et al., 2020; Megginson et al., 2019).

[14]Miner extractable value (MEV) is a measure of the profit a miner can make through the ability to arbitrarily include, exclude, or re-order transactions within the blocks they produce.

[15]Our arguments suggesting that the presence of CFs has a positive impact on startup firm performance are based on the idea that selling tokens and listing them on an exchange platform shows similarities with selling equity in an IPO (Fisch and Momtaz, 2020; Howell et al., 2020; Lyandres et al., 2022; Momtaz, 2020). A recurring theme in the IPO literature is the relationship between institutional investor backing and aftermarket performance, mostly concluding that IPOs backed by venture capital funds outperform non-venture-backed IPOs (Brav and Gompers, 1997; Krishnan et al., 2011; Levis, 2011).

Screening refers to an investor's selection of portfolio ventures. Venture funds, in particular, should have time, knowledge, and resources to assess the quality of projects by carrying out careful due diligence, verify the information provided by ventures, use sophisticated pricing and forecasting models, and implement effective contracting (Cumming et al., 2017; Gompers et al., 2020; Kaplan and Stromberg, 2001). The presence of funds also signals project quality and certifies legitimacy to other stakeholders such as employees, suppliers, and financial intermediaries, which triggers further performance increases (Hsu, 2004; Megginson and Weiss, 1991). Such certification may be particularly important in token markets, where a functioning institutional framework is largely missing, giving rise to moral hazard problems such as effort under-production (Chod and Lyandres, 2021).[16]

In addition, there is a treatment effect from the active involvement of institutional investors. Similar to venture capital funds (Cumming et al., 2017; Gompers, 1995; Hellmann and Puri, 2002; Puri and Zarutskie, 2012), crypto venture funds enhance project quality by performing both a monitoring and an advising function. They also provide access to investor networks, which is particularly valuable for all future financing rounds (Gompers, 1995). Because size and skills of CFs allow them to spend significant resources in acquiring and processing information, which empowers them to coordinate collective actions against shirking management teams (Tirole, 2001), they are able to generate value. Moreover, based on the hedge fund literature (Bebchuk et al., 2015; Brav et al., 2015), we expect that crypto hedge funds engage with and pressure a venture's management team in credible ways, seeking actions in the strategy and development of the project.[17]

Collectively, the *SFOH* posits that CF-backed startup firms are more successful than their non-CF-backed peer firms. We test this hypothesis along various performance dimensions *during* and *after* a token offering. First, we test whether CF backing has a positive effect on venture valuations. Second, we assess the long-term performance of token ventures with crypto fund backing in the secondary market relative to their peers without. Third, we measure the announcement effect when CF backing is disclosed in the secondary market for tokens. Formally, we test the following hypothesis:

Hypothesis 1a *CF-backed startup firms achieve higher valuations than non-CF-backed startup firms during token-based crowdfunding campaigns.*

[16]Certification requires the communication of a fund's participation in an ICO. However, because of the anonymity of DeFi solutions, investor identities remain unknown and are rarely publicized (Chen and Bellavitis, 2020; Fisch, 2019). Therefore, the certification effect funds can provide in an ICO context may be limited.

[17]Hedge fund involvement can take strong forms. For example, when so-called 'wolf packs' attack, hedge funds buy into the same target firm, do not formally coordinate their strategies, yet join forces to pressure incumbent management (Bessler et al., 2015; Brav et al., 2008). As such, even small investors can exert a large impact on long-term value if they manage to increase their bargaining power via herding effects.

Hypothesis 1b *CF-backed startup firms generate higher long-run performance than non-CF-backed startup firms after token-based crowdfunding campaigns.*

Hypothesis 1c *There are positive post-ICO valuation effects in response to the announcement of a CF investment.*

2.3.2 Crypto Fund Performance

Next, we change the object of our analysis from the venture level to the fund level and examine the *Crypto Fund Outperformance Hypothesis* (*CFOH*). Token offerings are characterized by a high degree of information asymmetry between entrepreneurs and investors. In the absence of adequate regulatory and oversight mechanisms that verify signals about venture quality ex ante and punish false signals or under-provision of effort ex post, there is high investment risk in this infant market (Chod and Lyandres, 2021; Howell et al., 2020; Momtaz, 2020). The information asymmetry problem is further aggravated by general uncertainty about an industry's prospects and the intangibility of the underlying assets (Gompers and Lerner, 2001; Leland and Pyle, 1977). Momtaz (2021d) finds that coin offerings have incentives to exaggerate the information disclosed in white papers to increase the chances of successful funding. Chod and Lyandres' (2021) theoretical model illustrates that information asymmetry frictions can make the token market a 'market for lemons.'

In contrast to retail investors, institutional investors may still profit from their privileged position that enables them to better understand a venture's quality and extract informational rents (Chemmanur et al., 2009; Demiralp et al., 2011; Lee and Wahal, 2004). Given CFs' resources to collect information, the skills of fund managers, and high-powered managerial incentive schemes[18], outperformance on the venture level should spill over to the fund level, i.e., funds can achieve abnormal returns through their active strategies such as venture oversight, coin selection, or market timing.

CFs operate in a nascent asset class. The mean fund in our sample has been in operation for less than four years (see Section 4.4). Analyzing traditional hedge funds, Aggarwal and Jorion (2010) find significant outperformance during the first three years of existence. Thereafter, performance tends to deteriorate. There are three possible explanations for superior performance in early years of existence.

First, emerging fund managers may have newer and better ideas for trades, and they are more nimble than established fund managers. Moreover, they have stronger incentive

[18]For example, PwC's (2021) survey among crypto hedge fund managers shows that the average management fee in their sample is 2.3% per year, and the average performance fee is 22.5%. These numbers come very close to the standard 2/20 rule in the hedge fund industry.

effects to build up reputation through above-average returns. Second, because emerging managers' initial wealth is lower, their marginal utility of performance incentives is likely to be higher during the first years. Third, good past performance generates money inflows and growth in assets under management, which leads to an erosion of fund performance over time provided there are diseconomies of scale (Berk and Green, 2004; Goetzmann et al., 2003; Pastor et al., 2015; Zhong, 2008). Getmansky et al. (2004) study competition in the hedge fund industry and confirm decreasing returns to scale.

Berk and Green's (2004) theoretical model, suggesting that all fund managers will have the same performance (after fees) in equilibrium, regardless of their skill, requires not only significant diseconomies of scale, but also that money is competitively allocated. The market for tokens is still in infancy, and capital is most likely not allocated purely on a competitive basis. For example, investors may give large weight to factors such as trust (Gennaioli et al., 2015) or make different investment choices depending on their level of sophistication (Gârleanu and Pedersen, 2018). If such forms of market segmentation are prevalent in the mutual fund industry, it is all the more likely that they undermine Berk and Green's (2004) prediction in token markets. In equilibrium, fund performance is then not only determined by competition between investors, but also by the skill of fund managers.[19] If managerial skill, rather than luck, explains CF outperformance, we should also observe performance persistence. In this case, past performance information is helpful in predicting future fund performance.

Taken together, the *CFOH* suggests that CFs outperform the market and generate value-added for investors. Their performance is persistent because managers bring special skills to the market for tokens. Formally, we test:

Hypothesis 2a *Crypto funds outperform the overall token market.*

Hypothesis 2b *As a sign of managerial skill, crypto fund outperformance is persistent.*

2.3.3 The Role of Investor Networks

Finally, we examine the moderating role of CFs' investor network centrality for the startup firm-crypto fund investment relationship. According to the *Investor Network Hypothesis* (*INH*), the structure of an investor's network can influence the dynamics of information diffusion as well as the visibility of each investor's actions (Bajo et al., 2020). In particular,

[19]As shown in Table 9, the average CF in our sample holds only a small number of coins. CFs tend to be concentrated, with weights that differ strongly from the market benchmark. Mutual funds with more concentrated portfolios show better performance (Choi et al., 2017; Huij and Derwall, 2011; Kacperczyk et al., 2005). Similarly, funds with a high active share, i.e., funds with portfolios that strongly differ from their benchmarks, possess skills and outperform (Cremers and Petajisto, 2009; Sun et al., 2012).

the position of a fund in the entire network of CFs is interpreted as a proxy of its relative influence, prominence, and prestige (Davis and Robbins, 2005).

The social network literature finds that network structures play an important role in disseminating information (Banerjee, 1992; Bikhchandani et al., 1992). Fracassi (2017) shows that more centrally located managers have better access to information, which enables them to make better corporate policy decisions. Similarly, we evaluate the position of a fund in the network of all CFs by counting the number of investment ties with other CFs; this is the so-called degree centrality (Borgatti, 2005).

Because of their superior ability to gather and process information, CFs that are more central in the network of all CFs convey more valuable information through their trading. Because of their privileged position in the network and the associated ease of information transmission, more central CFs also have greater monitoring abilities. More central CFs extract information from other investors, and these network contacts enable them to provide more valuable strategic advice and coaching (Bertoni et al., 2011; Gompers, 1995).

To the extent that the activities of more central CFs assist their portfolio ventures to enhance value, this should also be reflected in better fund performance (Ozsoylev et al., 2014). The *INH* suggests that the positive performance effects in our previous hypothesis, the *SFOH* and the *CFOH*, are moderated by a CF's network centrality:

Hypothesis 3 *The positive valuation effects in Hypotheses 1a/1b/1c (startup level) and 2a/2b (fund level) are increasing in CFs' network centrality.*

3 Data and Methods

3.1 Data Sources

To the best of our knowledge, no prior study examines a sample that combines CF-level with startup-level characteristics, performance data, and aftermarket events. One plausible reason for this research gap pertains to data-related barriers. Our empirical analysis is based on four major data sources combined with hand-collected data, additionally requiring a substantial manual effort to link observations across these different data sources. The main building blocks of our sample are as follows:

1. Crypto fund data: CF data comes from *Crypto Fund Research*, a company that functions as an information aggregator and information intermediary in the CF industry. Fund characteristics and monthly returns are available for 343 CFs from January

2017 to September 2020. To ensure a high level of data completeness, we hand-collected as many missing variables as possible from various websites (e.g., the CFs' own websites and *LinkedIn*). Data from *Crypto Fund Research* has already been used in Fisch and Momtaz's (2020) study to identify whether an ICO firm was CF-backed. We are the first to examine CFs' monthly returns, fund-level characteristics, and their impact on startup performance.

2. ICO and startup data: ICO- and startup-level data comes from the *Token Offerings Research Database* (*TORD*)[20], which aggregates data from various sources, including *ICObench*, *ICOmarks*, *GitHub*, *LinkedIn*, among others. The *TORD* contains more than 6,000 ICO firms. For each TORD-ICO firm, we manually created a unique mapping to the *Crypto Fund Research* database.

3. Token price data: Token performance data in the secondary market comes from *CoinMarketCap*. We retrieve token prices, market capitalizations, and trading volumes until October 2020. These data enable us to construct composite token market indices as benchmarks, which we use to measure CF-level and startup-level abnormal returns. For each available token on *CoinMarketCap*, we manually created a concordance table linking token prices to startups in the *TORD*.

4. Secondary market investment data: We use voluntary disclosure of aftermarket CF investments in post-ICO firms from *Crunchbase* to identify 1,065 such events until October 2020. We retrieve information on the CF, the startup, and the investment date. These observations are manually merged to our CF-level and startup-level databases.

We are able to match token price performance data from *CoinMarketCap* to 1,282 *TORD* firms (an overlap rate of 19.9%). For our baseline model for the effect of CF backing on startup valuation, 1,226 observations remain with a complete set of variables. This represents one of the largest samples in the ICO literature. For all subsequent tests, sample sizes vary, but we always use the largest possible sample that remains after several matching steps. All variables are defined in Table A1 in the Appendix.

3.2 Variables

3.2.1 Performance Measurement: Startups

We measure the performance of tokenized startups in three ways. First, in line with existing ICO studies (Fisch, 2019), we measure ICO firm valuation as the natural logarithm of

[20]Available from www.paulmomtaz.com/data/tord.

the total amount raised (in $ million). Second, buy-and-hold abnormal returns (BHARs) in the secondary market are calculated by subtracting the market benchmark buy-and-hold return from a startup 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 use a value-weighted token market index. All results are robust to equally- and liquidity-weighted benchmarks. Third, we measure cumulative abnormal returns (CARs) around CF investment announcements in the aftermarket. In particular, we assess the impact of CF investment announcements on token price performance in public secondary markets over various event windows, ranging from [–5,+5] to [–15,+15] in days, with $t = 0$ as the announcement date. Cumulative token returns are adjusted for the market benchmark return over the same event window.

3.2.2 Performance Measurement: Crypto Funds

Performance on the CF-level is measured in various ways. First, the CAPM-alpha is defined as a fund's average monthly return in excess of the expected return. The value-weighted token market index (VW-index) serves as our main benchmark. Formally, fund i's alpha in month t is fund return minus expected return: $\alpha_{it,VW} = r_{it} - (r_{ft} + \beta_{i,VW} \times (r_{mt,VW} - r_{ft}))$ where r_{it} denotes the raw return of fund i in month t, r_{ft} the risk-free rate (one-month U.S. Treasury-Bill), $\beta_{i,VW}$ is the beta of fund i relative to the VW-index, and $r_{mt,VW}$ is the value-weighted token market return. $\beta_{i,VW}$ is estimated in a CAPM-like regression as $\frac{Cov(r_{it}, r_{mt,VW})}{Var(r_{mt,VW})}$, and $r_{mt,VW}$ is defined as $\sum_{j=1}^{N} r_{jt} \times \frac{MCap_{jt}}{\sum_{j=1}^{N} MCap_{jt}}$, where r_{it} is the return of token i in month t, and $MCap_{it}$ denotes the market capitalization of this coin at the beginning of month t. Second, as an alternative performance measure, we compute the Sharpe ratio (SR) as a fund's alpha divided by the standard deviation of the fund's alpha. Both α and SR are reported using value-, equally-, and liquidity-weighted market adjustments.

Third, based on the funds' CAPM-alphas, we analyze their performance persistence. Similar to Nanda et al. (2020), we measure CF performance persistence as the fraction of positive alphas in two consecutive time periods. For example, to compute the performance persistence in year two vis-à-vis year one, our proxy for managerial skill is defined as the ratio $\sum_{\text{Month} \in \{13,24\}} \mathbb{1}[\alpha > 0]/12 / \sum_{\text{Month} \in \{1,12\}} \mathbb{1}[\alpha > 0]/12$.

3.2.3 Independent Variables

Our main explanatory variable, denoted as *Crypto fund* (*CF*), is a dummy variable that is equal to one if a startup has secured CF backing for an ICO, and zero otherwise. Moreover, we define two categories of CF investment strategies, which are based on CF information disclosed by *Crypto Fund Research*. First, *Venture-style capital* is a dummy variable equal to one if at least one invested CF pursues a venture-style investment strategy, and zero otherwise. Second, *Hedge fund-style capital* is a dummy variable equal to one if at least one invested CF follows a hedge fund-style investment strategy, and zero otherwise.

Moreover, we define two fund categories based on investment scope. *Specialization* is a dummy variable equal to one if at least one invested CF maintains a specialized investment scope, and zero otherwise. All funds are classified as either specialized or diversified based on the median number of investments of all funds (i.e., below-median classifies a CF as a specialized fund). *Diversification* is a dummy variable equal to one if at least one invested CF follows a diversified investment scope, and zero otherwise.

We construct a variable for investor network centrality as a moderator in our analyses. In particular, the variable *CF investor network centrality* refers to the number of a fund's direct connections to other CFs through their combined token investments. Following Bajo et al. (2020), we measure a fund's investor network centrality by using the number of first-degree connections to other CFs through investments in the same startups.[21]

Finally, we use a large set of control variables in our regression models. These variables are related to firm characteristics, offering characteristics, market characteristics, human capital characteristics, and additional CF characteristics. For the sake of brevity, all these variables are described in detail in Table A1 in the Appendix.

3.3 Summary Statistics: Key Variables

Summary statistics for our outcome variables and the comparison between CF-backed and non-CF-backed startups are shown in Table 1. The average startup raises $3.11 million (log.=14.95; log. SD=2.00), and experiences BHARs of 6.3% (SD=260%), –17.7% (SD=218%), –34.8% (SD=170%), and –40.8% (SD=145%) for holding periods of 6, 12, 18, and 24 months, respectively. The average CAR associated with CF investments in the secondary market is 4.4% (31.6%) over the [–5,+5] event window. The average CF has a monthly value-weighted CAPM-alpha of 2.69% (SD=25.3%) and a Sharpe ratio of 0.12 (SD=0.12). The positive CAPM-alphas are persistent with an average proxy value of 1.03 (SD=0.44).

A comparison of the outcome variables between CF-backed and non-CF-backed startups indicates that CF-backed startups outperform their non-CF-backed peers. On average, CF-

[21]The network degree (d) for CF i is defined as $d_i = \sum_{j=1,j\neq i}^{N} x_{ij}$, where N is the total number of CFs (nodes), x_{ij} an element (edge) in the adjacency matrix, i the row-indicator for one fund, and j the column-indicator for another fund. If the CFs i and j are invested in the same startup, x_{ij} is equal to one, zero otherwise. In a similar way, we also construct a variable for the network centrality of the ICO team.

backed startups raise more (log. Δ=1.66), perform better in the long run with differences in mean BHARs of 111.1%, 55.9%, 44.2%, and 53.3% for holding periods of 6, 12, 18, and 24 months, respectively, and a difference in the average announcement-related CARs of 2.0%. All differences in means, except that for the CARs, are statistically significant with p-values below 1%.

[Place Table 1 about here]

3.4 Summary Statistics: Fund Characteristics and Control Variables

Summary statistics on CF characteristics and control variables for our aggregate sample of *TORD* firms are presented in Table 2. 6.2% of all startups receive crypto fund backing. Thereof, crypto hedge funds and crypto venture funds invest in 2.3% and 5.1% of the startups in our sample, respectively. Similarly, specialized and diversified funds back 2.2% and 4.9% of all sample startups, respectively.

The average startup receives an *ICObench* aggregate rating of 2.9 (SD=0.8), 51% of all sample startups post open source codes on *GitHub*, the business model of 48.2% of all ventures involves platform building, the average startup targets 2.9 (SD=2.4) distinct industries as per *ICObench*'s industry classifications scheme, and 87.2% of all tokenized startups are built on the *Ethereum* blockchain. The average firm's team size is 10.7 (SD=7.3), with 2.9 (SD=2.9) technical team members, and 0.6 (SD=1.1) members with a Ph.D., and 4.3 (SD=3.6) with previous crypto experience.

Of all ICOs in our sample, 49.3% were preceded by a pre-sale event, while only 6.6% and 26.4% of them involve bonus and reward schemes, respectively. 41.6% of all ICOs involve a Know-Your-Customer (KYC) process. The average number of competing ICOs is 771 (SD=525). With respect to market cycles, 21%, 52.4%, and 24.9% of the sample ICOs took place during bull, bear, and sideways market phases, respectively. Finally, the sample means for the network centrality measures of CFs and startups are 97 (SD=57) and 28 (SD=40), respectively.

[Place Table 2 about here]

3.5 Correlations

Pairwise correlation coefficients for all variables are presented in Tables A2 and A3 in the Appendix. In all regressions, as in Leitterstorf and Rau (2014), we make sure that Variance Inflation Factors (VIFs) do not exceed the commonly agreed threshold of five.

3.6 Econometric Approach

A substantial part of our empirical analysis evaluates the effect of CF backing on the short- and long-term performance of blockchain-based startups. In our baseline regressions, we estimate the impact of CF backing on startup i, using the CF_i dummy, on the dependent variables, DV_i, defined as funding valuation during the ICO ($Valuation_i$) or the buy-and-hold abnormal return ($BHAR_i$) over 24 months after the ICO. We further control for a set of independent variables, labelled Ω_i:

$$DV_i = \beta CF_i + \Omega_i \gamma + \varepsilon_i, \quad DV_i \in \{\textit{Valuation}_i, \textit{BHAR}_i\} \tag{1}$$

A natural concern with Equation (1) is that $\hat{\beta}$, the estimator of the effect of CF backing on startup performance, suffers from an endogenity bias. As already discussed above, we are interested in the treatment effect that CF backing has on startup performance, while controlling for the selection effect. Controlling for the selection effect is important because CF have the skills and resources to screen the market and perform due diligence more efficiently than crowd-investors (Bertoni et al., 2011; Colombo and Grilli, 2010; Fisch and Momtaz, 2020; Guo and Jiang, 2013). To deal with the non-exogenous nature of CF backing and control for the selection effect, we use three different estimation approaches: (i) inverse Mills ratio (IMR model), (ii) propensity score matching (PSM model), and (iii) generalized residuals (GR) as instrumental variables (IV model).

All three approaches require the estimation of a selection model in the first stage. This selection model predicts the probability that startup i receives CF backing using a vector of exogenous control variables influencing the selection mechanism, $\Omega_i^{(s)}$:

$$CF_i = \Omega_i^{(s)} \delta + \xi_i \tag{2}$$

These 'selection probabilities' are then transformed and included in the second stage models, which estimate the treatment effects of interest.

IMR model. Our first empirical approach uses an inverse Mills ratio. Based on the selection model in Equation (2), and consistent with Colombo and Grilli (2008) and Heckman and Navarro-Lozano (2004), we calculate the IMR for startup i, denoted as IMR_i:

$$IMR_i = \frac{\phi\left(\Omega_i^{(s)} \delta\right)}{\Phi\left(\Omega_i^{(s)} \delta\right)} \tag{3}$$

where $\phi(.)$ and $\Phi(.)$ denote the probability density function and the cumulative density function of the standard normal distribution, respectively. In the second stage, IMR_i is added to the main model in Equation (1), in which the coefficient λ tests the null hypothesis that no selection effect exists:

$$DV_i^{IMR} = \beta CF_i + \lambda IMR_i + \Omega_i \gamma + v_i, \quad DV_i^{IMR} \in \{\textit{Valuation}_i^{IMR}, \textit{BHAR}_i^{IMR}\} \tag{4}$$

PSM model. Our second approach matches on the IMRs. We use a PSM model to address the problem that inclusion of the IMR in the second stage does not eliminate the selection bias, e.g., if the remaining selection process does not follow a normal distribution. This can occur if the conditional independence assumption, the implicit assumption that CF backing is independent of the other control variables conditional on IMR_i, is violated.

We employ the PSM model using the nearest-neighbor algorithm (Dehejia and Wahba, 2002; Rosenbaum and Rubin, 1983). The model only considers those ventures without CF backing (the control group) that are most similar to those ventures with CF backing (the treatment group). Provided that ventures with similar observable characteristics should also be more similar in their unobservable characteristics, the conditional independence assumption in this matched sample is less likely violated, mitigating endogeneity concerns.

IV model. Our third approach computes GRs based on the selection model and utilizes them as instrumental variables in the IV model. This model helps to deal with endogeneity generated by spurious correlation from omitted variables or reverse causality, leading to the 'experimental average treatment effect' (Heckman, 1990) of CF backing on ICO performance. In line with Gourieroux et al. (1987), the generalized residual for startup i, GR_i, is defined as:

$$GR_i = CF_i \times \frac{\phi\left(-\Omega_i^{(s)}\delta\right)}{1 - \Phi\left(-\Omega_i^{(s)}\delta\right)} + (1 - CF_i) \times \frac{-\phi\left(\Omega_i^{(s)}\delta\right)}{\Phi\left(-\Omega_i^{(s)}\delta\right)} \tag{5}$$

where again $\phi(.)$ and $\Phi(.)$ are the probability density function and the cumulative density function of the standard normal distribution, respectively. We restrict the standard deviation of the error term for ventures with CF backing to be equal to that of ventures without CF backing (Colombo and Grilli, 2005). This restriction ensures that GR_i can be added as an instrumental variable for the CF backing dummy in Equation (1). For this approach, we report the Wald test statistic to assess the overall model fit.

4 Empirical Results

4.1 Crypto Funds and Startup Firm Valuation

4.1.1 Valuation Effect: Main Results

Table 3 shows regression results for the effect of CF backing on startup firm valuations. The dependent variable is the natural logarithm of the funding amount (in $) in models (1), (3), (4), (5), and an indicator variable for whether a startup is backed by a CF in model (2). Model (1) estimates the effect of CF backing on ICO firm valuation without controlling for the potential selection bias. Model (2) explicitly models the selection mechanism, and models (3), (4), and (5) are the second-stage regressions that rely on Inverse Mills Ratios (IMR), propensity score matching (PSM), and instrumental variables (IV), respectively, to control for selection-related endogeneity. We further control for our comprehensive list of firm, issuance, market, and human capital-related factors. All models include country and quarter-year fixed effects. The adjusted R^2 exceeds 20% in all models, which is consistent with existing studies (Fisch, 2019; Fisch and Momtaz, 2020).

Overall, the results suggest that CF backing has a significantly positive effect on startup firm valuations in ICOs, supporting Hypothesis 1a. The coefficients on the CF dummy variable in the second-stage regressions are consistent across the various model specifications and range from 0.942 to 1.047, statistically significant with p-values below 1%. In economic terms, the estimates indicate that the average CF-backed firm achieves a valuation that is more than two-and-a-half times ($\approx e^{0.942}$) higher than that of its hypothetical non-CF-backed twin. The estimates are in line with anecdotal evidence that CFs demand a discount of 50 to 70% on the token value in private transactions, which startup firms often grant in anticipation of CFs' positive valuation effects in public transactions (Momtaz, 2022).

We also note that the estimate on *Crypto fund* in model (1) of 1.004 closely corresponds to those in models (3) to (5), suggesting that a potential selection bias does not strongly confound our baseline OLS estimate. This is further confirmed in model (3), where we find that the IMR coefficient (not tabulated) is statistically insignificant, also implying that the treatment effect of CF backing on ICO firm valuation is not significantly biased — at least in a statistical sense — by any underlying selection effect. Nevertheless, we find in the selection model in column (2) that several variables are able to predict whether a startup firm receives CF backing. In particular, expert ratings, platform business models, pre-sales, reward-related promotion schemes, the number of competing ICOs, market volatility, as well as team members with a technical background or a Ph.D. have some prediction power for CF backing in our sample.

For the control variables in the valuation models (1), (3), (4), and (5), we report regression coefficients that are largely consistent with those in related studies (Belitski and Boreiko, 2021; Bellavitis et al., 2020; Fisch, 2019; Momtaz, 2020). We find that expert ratings and team size have significantly positive effects on ICO valuation, while open-sourced code, the number of targeted industries, reward-related promotion schemes, the number of competing ICOs, and the number of team members with a technical degree are negatively related to the funding amount in several model specifications. Finally, we note that the estimated coefficients on the control variables are consistent when we adapt our regression models, e.g., to different combinations of independent variables, and thus we suppress the estimates in all subsequent analyses for the sake of brevity.

[Place Table 3 about here]

4.1.2 Valuation Effect: The Role of Investment Strategy and Scope

Next, we test whether the valuation effect of CF backing is sensitive to CFs' investment strategies (venture-style vs. hedge fund-style) and investment scope (specialization vs. diversification). The results are shown in Table 4. The models correspond to those in Table 3, with the exception that the CF indicator is replaced as the independent variable with proxies for investment strategy and investment scope. Panel A and B in Table 4 show OLS, IMR, and IV model estimates for the investment strategy and scope, respectively.

For investment strategy, the estimates suggest that the valuation effects are more pronounced for venture-style than for hedge fund-style CFs. The second-stage regression coefficients for the ventures-style indicator range from 0.809 to 0.860, statistically significant with p-values below 1%. In contrast, the hedge fund-style indicator is substantially smaller, ranging from 0.416 to 0.434, and less significant in statistical terms. The corresponding coefficient in the IMR and IV models are only marginally significant at the 10% level. Therefore, the positive valuation effect of CF backing is primarily driven by venture-style CFs.

For investment scope, we find that diversified CFs are responsible for the positive valuation effect. The specialization indicator remains inconsistent (with marginally significantly positive coefficients in the OLS and IMR models, but an insignificantly negative estimate in the IV model). In contrast, the diversification indicator is significant in statistical and economic terms in all second-stage regressions, ranging from 0.890 to 1.413, with p-values below 1%. Overall, we conclude that investment strategy and scope matter for the valuation effects of CF backing in important ways. In particular, venture-style and diversified CFs account for the positive valuation effect in the full sample.

[Place Table 4 about here]

4.2 Crypto Funds and Startup Firm Post-Funding Performance

4.2.1 Performance Effect: Graphical and Univariate Evidence

Our previous results indicate that CF backing has a positive valuation effect in ICOs. In this section, we test whether CF backing also has a longer run effect on token price performance over a 24-month period subsequent to a token exchange listing. Figure 2 plots monthly buy-and-hold abnormal returns (BHARs), using equally-, value-, and liquidity-weighted market benchmarks. Panel A plots BHARs for the full sample of startup firms, while Panel B depicts BHARs only for CF-backed startup firms.

Two observations are noteworthy. First, BHARs are continuously downward-sloping during the 24-month time period, which resembles a well-known pattern from the IPO long-run underperformance literature (Ritter, 1991). Second, underperformance is clearly more pronounced for the full sample (Panel A) than for the sample that includes only CF-backed startup firms (Panel B). This is first evidence that CF-backed startup firms outperform their non-CF-backed peers in the long run. BHARs are more negative when the equally-weighted benchmark adjustment is used, which is driven by a relative overweighting of very small tokens offerings in the composite market index. [22]

[Place Figure 2 about here]

Table 5 confirms that CF-backed startup firms outperform in terms of BHARs in our univariate comparison. It shows tests for differences in means and medians between BHARs for the 6-, 12-, 18-, and 24-month investment periods, using equally-, value-, and liquidity-weighted benchmarks to compute abnormal returns. The results show that, independent of the risk adjustment and the investment period, CF-backed startup ventures always outperform non-CF-backed startup firms. The outperformance for the mean is significantly higher than that for the median startup firm, e.g., 53.29% vs. 5.93% after 24 months for value-weighted BHARs. Given these univariate results, we next examine whether the long-run outperformance of CF-backed startup firms is robust in a multivariate setting when we also control for a potential selection bias.

[22] These findings are consistent with Fisch and Momtaz (2020) and extend their results to longer investment horizons and alternative risk adjustments.

[Place Table 5 about here]

4.2.2 Performance Effect: Main Results

Table 6 presents our results from testing the treatment effect of CF backing on 24-month BHARs, using a value-weighted benchmark, in regressions that control for potential selectivity and various confounding factors. The econometric approach is identical to that in Table 3, with only the dependent variable in models (1), (3), (4), and (5) being replaced. The sample size decreases notably from 1,226 in Table 3 to 361 tokens in Table 6 because many startup firms have not had their tokens listed on a secondary market for at least 24 months at the time of compiling this sample.

The second-stage regression results support Hypothesis 1b that CF backing has a significantly positive effect on token price performance in the aftermarket. The coefficients in models (3) to (5) range from 0.166 to 0.251, and they are statistically significant at the 5% level. Therefore, startup firms with CF backing outperform those without CF backing at least by 16.6% over the investment horizon of 24 months. In robustness tests (not reported), we find that these results are similar for shorter investment horizons and for alternative risk adjustments (i.e., using the equally- and liquidity-weighted benchmarks). Moreover, the coefficient in the OLS model (1) of 0.178 is similar to the corresponding second-stage coefficients, suggesting that selectivity does not confound our identified effect in a material way.

All control variables are weak predictors of BHARs. Only the estimated coefficients on expert rating and team size are statistically significant in three and two of our models, respectively. This observation resonates with the finance literature that long-run returns are difficult to predict based on firm fundamentals (Brennan et al., 1998).

[Place Table 6 about here]

4.2.3 Performance Effect: The Role of Investment Strategy and Scope

Table 7 reports whether our proxies for CFs' investment strategy (venture- vs. hedge fund-style) and investment scope (specialization vs. diversification) have differential effects on the 24-month BHARs (again using the value-weighted benchmark). The analyses are analogous to those in Table 4. However, the results for long-term, risk-adjusted token price performance in Table 7 are opposite to the effects of CFs' investment strategy and scope on startup valuation in Table 4.

In particular, analyzing investment strategies, venture-style CFs have a non-significant effect on 24-month BHARs, with estimates ranging from 0.015 to 0.065. Long-term token price outperformance of CF-backed startup firms is largely driven by hedge fund-style CFs. The estimates range from 0.268 to 0.432, statistically significant with p-values below 5% for the OLS and IMR models, and below 10% for the IV model. For example, the IMR model suggests that investors earn a 26.9% higher risk-adjusted return after holding tokens of a startup firm that is backed by a hedge fund-style CF for two years.

With respect to investment scope, it is fund specialization that is positively related to the 24-month BHARs, while fund diversification has a non-significant effect. The estimated coefficients for specialization are also more significant in economic terms compared to those for diversification; the estimates range from 0.146 to 0.315 (specialization) vs. 0.064 to 0.209 (diversification). For example, the average startup that is backed by a specialized CF delivers a 31.5% higher BHAR after a two year holding period according to the IMR model.

The combined results in Tables 7 and 4 suggest that investment strategy and scope differ in their effects on startup firm valuation and aftermarket performance. While venture-style and diversified CFs have a positive effect on token valuation at issuance, hedge fund-style and specialized CFs have a positive effect on aftermarket performance in the long term after the ICO took place.

[Place Table 7 about here]

4.3 Event Study: Announcement Returns in the Secondary Market

Next, we examine whether the positive performance effect of CFs also shows up in an event study setup. We measure token returns associated with the post-ICO announcement of a CF investment in the secondary market. Figure 3 shows that token prices react positively to the announcement of a post-ICO fund investment. The lines show the daily token returns net of the returns of equally-, value-, and liquidity-weighted market benchmarks over the [–15,+15] event window (in days), with $t = 0$ as the identified announcement date. The patterns are similar for the various benchmark adjustments. Token prices start to react to the news three to four days before the actual announcement date.[23] The announcement-

[23]We remain agnostic about whether these pre-announcement returns are anticipatory effects associated with information leakage or measurement error. Tokens are legally classified as 'non-securities,' and their exemption status from securities law also exempts them from disclosure obligations related to institutional investments. For this reason, it is possible that startup firms and CFs communicate post-ICO investments through different channels on different days. For the purpose of our analysis, we manually researched announcements on the internet and always defined the earliest identified announcement as $t = 0$.

related abnormal token return peaks around day four, and it subsides over the subsequent five to ten days. We conclude that the news of post-ICO CF investments are incorporated into token prices rather slowly over a period of two to three weeks.

We formally test for the difference in pre- and post-announcement abnormal returns in Table 8. Pre-announcement average daily abnormal returns are close to zero, while post-announcement average daily abnormal returns are, in a statistical sense, significantly different from zero. The difference in daily average announcement-related abnormal returns is 1.37%, 1.45%, and 1.50% for the value-, equally-, and liquidity-weighted benchmarks, respectively, with statistical significance at the 10% level. Accumulating these abnormal returns over the eleven-day [–5,+5] event period leads to sizeable outperformance, ranging from 15.07% to 16.50%. Therefore, corroborating Hypothesis 1c, startup firms benefit from post-ICO CF investments in the secondary market for tokens.

[Place Figure 3 about here]

[Place Table 8 about here]

Taken all results together, they provide support for the *Startup Firm Outperformance Hypothesis (SFOH)*. In particular, CF-backed startup ventures obtain higher ICO valuations, outperform their peers in the long run, and benefit from token price appreciation around CF investment disclosure in the secondary market. We expect that these positive performance effects also translate into a beneficial impact on CF performance itself. Therefore, we proceed by changing the focus of our analysis from the venture level to the fund level.

4.4 The Performance of Crypto Funds

4.4.1 Crypto Fund Characteristics and Performance

Because this is the first study of CFs, a new intermediary in entrepreneurial finance with a rapidly growing market presence, we preface our CF performance results with a discussion of the characteristics of our CF sample. Summary statistics are shown in Panel A in Table 9. The number of observations, reported in the last column of Panel A, varies because CFs are not yet subject to regulated disclosure obligations, and therefore we have to rely on voluntarily disclosed fund characteristics.

The average (median) CF in our sample makes 16.5 (14) investments, has assets under management in the amount of $97 million ($40 million), and is operating for 3.8 (3.3) years as of September 2020. Interestingly, the for hedge funds typical 2-20 fee structure is the most commonly used compensation scheme for CFs, resulting in a mean (median) performance incentive (i.e., the ratio of a fund's performance fee to its management fee) of 11.6 (10). Roughly one-third of all CF employees have crypto-industry experience or investing experience prior to joining the fund, and 14% hold a Ph.D. The average (median) CF investor network centrality is 127 (126), indicating, e.g., that the average fund has 127 direct connections to other CFs through their combined token investments.

CF performance, based on CAPM-alphas and Sharpe ratios using value-, equally-, and liquidity-weighted benchmark adjustments, is presented in Panel B of Table 9. Average monthly CAPM-alphas range from 2.52% to 2.71% and are statistically significant, with p-values below 1% (based on t-tests). Median CAPM-alphas are even higher in a range between 2.74% and 3.34%, also statistically significant with p-values below 1% (based on Wilcoxon-tests). Therefore, investors in the mean (median) CF can expect a monthly outperformance of at least 2.52% (2.74%) relative to the composite market benchmark. At the same time, standard deviations consistently above 25% indicate that CF outperformance comes at relatively high risk. However, the standard deviation of the three market benchmarks (not reported) ranges from 30% to 37% during our sample period, showing that the mean CF is able to reduce performance volatility despite a smaller degree of diversification. The positive risk-return profile is further confirmed by a positive Sharpe ratio of 0.12, irrespective of the risk-adjustment method. Overall, these results confirm Hypothesis 2a that CFs are able to outperform the token market on a risk-adjusted basis. From a theoretical perspective, they also support the risk transformation function of CFs as intermediaries that reduce participation costs for investors (Allen and Santomero, 1998).

[Place Table 9 about here]

4.4.2 Crypto Fund Performance Persistence: Skill vs. Luck

Next, we address the question whether the average CF outperforms because of *skill* or *luck*. We follow the methodology in Nanda et al. (2020) and test how the fraction of months in which a fund was able to outperform the market in its initial investment period correlates with this same fraction in a subsequent period. Intuitively, if CFs possess skills that explain their outperformance, this correlation should be high, and thus their ability to outperform the market will be persistent. In contrast, there should be no performance persistence in the case of luck. The results of performance persistence regressions are shown in Table 10.

We find that CFs' positive abnormal returns are persistent, supporting Hypothesis 2b that CFs possess skills that enable them to persistently outperform. The first two columns test whether the fraction of positive CAPM-alphas in the first six months of a fund's lifetime

($\sum_{\text{Month}\in\{1,6\}} \mathbb{1}[\alpha > 0]/6$) predicts the fraction of positive CAPM-alphas over the next twelve months ($\sum_{\text{Month}\in\{7,18\}} \mathbb{1}[\alpha > 0]/12$). Column (1) includes quarter-year fixed effects, and column (2) adds fund-level and human-capital controls. The regression models in columns (3) and (4) test the same, with the exception that the initial period consists of twelve instead of only six months.

All estimated coefficients of interest are significantly positive, suggesting that CFs' outperformance is persistent. As an example, the coefficient in the first column of 0.320 is statistically significant with a p-value below 1%, suggesting that the probability that a CF outperforms the market during months seven to eighteen is 32% higher if it already outperformed in months one to six. These results are based on CAPM-alphas measured using the value-weighted market benchmark. They also remain robust (not tabulated) when we use equally- or liquidity-weighted benchmarks to compute risk-adjusted performance. Taken together our results confirm the *Crypto Fund Outperformance Hypothesis (CFOH)*, i.e., CFs beat the market, on average, and their outperformance is persistent, suggesting that funds deliver abnormal returns because of skill, rather than sheer luck.

[Place Table 10 about here]

4.5 The Role of the Investor Network

The results indicate that startup firms benefit from CF backing in terms of higher token valuations during ICOs, higher token returns post-ICO, and token price appreciations when CF investments are announced in the secondary market. Similarly, CFs benefit from investing in startups by generating positive abnormal returns for their investors. In a final step, we now investigate a potential channel for the mutually beneficial startup firm-crypto fund investment relationship: the investor network.

Regression results for the effect of *CF network centrality* on startup firm-related success measures and CF-related performance measures are shown in Panels A and B of Table 11, respectively. The coefficients on CF investor network centrality in Panel A are 0.004, 0.012, and 0.005 for predictions of startup firm valuations in ICOs (column (1)), 24-month BHARs (column (2)), and cumulative announcement-related abnormal returns relative to the value-weighted benchmark over the [–5,+5] event window (column (3)), respectively. The results are statistically significant at least at the 10% level.

These estimates are statistically significant and also economically meaningful. For the hypothetical scenario of two identical CFs, which only differ in that one fund takes an investor network position that is one standard deviation more central than the other, CF-backed startups benefit from a higher investor network centrality. Ceteris paribus, and consistent with both a certification and a monitoring effect, these startups receive a 25.6% higher token valuation, a 68.4% higher BHAR over the subsequent 24-month investment period, and a 28.5% higher CAR associated with fund investments in the secondary market. In contrast, the startup team network centrality variable is insignificant in all models.

Similarly, a CF shows a better performance itself when it is more central in the network of all CFs. As shown in Panel B, the investor network centrality coefficients are 0.020, 0.083, and 0.038 for predictions of monthly CAPM-alphas (column (4)), Sharpe ratios (column (5)), and our performance persistence measure (column (6)), respectively. In economic terms, for example, increasing a CF's investor network centrality by one standard deviation is associated with an increase in the mean monthly CAPM-alpha from 2.69% to 4.07%. This improvement is statistically significant with a p-value below 1%.

Overall, as predicted by the *Investor Network Hypothesis (INH)*, investor network centrality is positively and consistently related to all startup firm- and CF-related outcome variables used throughout our empirical analyses. In particular, supporting Hypothesis 3, we conclude that the investor network is an important economic channel that explains the mutually beneficial investment relationship between startup firms, CFs, and fund investors.

[Place Table 11 about here]

5 Discussion and Concluding Remarks

5.1 Summary of Main Results

This paper tests three overarching hypotheses pertaining to the role of crypto funds (CFs) *during* and *after* token-based crowdfunding campaigns, also known as Initial Coin Offerings (ICOs). The empirical context is intriguing because CFs are a new type of intermediaries in entrepreneurial finance markets that blend venture- with hedge fund-style investment strategies in primary and secondary markets for tokens. The first hypothesis, the ***Startup Firm Outperformance Hypothesis*** (***SFOH***), posits that CF-backed startup firms are more successful than non-CF-backed startups *during* and *after* token-based crowdfunding campaigns along various performance dimensions. The second hypothesis, the ***Crypto Fund Outperformance Hypothesis*** (***CFOH***), suggests that CFs outperform the the overall token market, and that their outperformance is persistent because they bring important skills to the market for tokens. Finally, the third hypothesis, the ***Investor Network Hypothesis*** (***INH***), proposes that the positive performance effects in the ***SFOH*** and the ***CFOH*** are driven by the CFs' investor network centrality.

Empirical evidence from a large sample of startup firms and crypto funds over the 2017-2020 period strongly support the ***SFOH***, ***CFOH***, and ***INH***, and mostly permit a causal interpretation. For the ***SFOH***, we find that CF backing (i) increases the ICO valuation, (ii) improves post-funding, risk-adjusted token price performance, and (iii) leads to positive announcement effects if CF backing is disclosed in the secondary market for tokens. For example, the average CF-backed startups' token price has outperformed that of non-CF-backed startups by 17% in terms of buy-and-hold abnormal returns (BHARs) within the first two years after the token exchange listing. We employ several two-stage and instrumental variable approaches to address potential endogeneity concerns, and confirm that startup firm outperformance is due to a treatment effect of CFs, rather than a selection effect. We are also able to study the impact of CFs' investment strategies on startup firm performance, and find that venture-style strategies drive the positive ICO valuation effect, while hedge fund-style strategies are the reason behind the positive post-funding token price performance. Additional evidence to support a causal interpretation comes from an event-study approach. If a startup firm announces post-ICO CF backing when it is already traded in public secondary markets for tokens, the token price appreciates by 15% during the eleven-day event window around the announcement.

For the ***CFOH***, we report that CFs outperform the market by 2.69% per month, as measured by the traditional CAPM-alpha. CFs' performance is even persistent over subsequent investment periods, suggesting that the their outperformance is due to skill, rather than luck. Finally, for the ***INH***, we measure CFs' network centrality, and show that it is the access to a broader investor network that is the driving force behind the outperformance of CF-backed startup firms and CFs themselves. CFs' investor network centrality is positively related to startup firms' ICO valuations, their BHARs after token issuance, and CF investment announcement returns in the secondary market. Similarly, it drives CFs' own investment performance in terms of CAPM-alphas, Sharpe ratios, and persistence.

As discussed next, these results contribute in important ways not only to the emerging token-based crowdfunding and crypto fund literatures, but also to the broadly established entrepreneurial finance literature by exploiting institutional features of our empirical context to provide novel insights into previously unexplored relations.

5.2 Theoretical Contributions and Practical Implications

Our study contributes to the entrepreneurial finance literature in several important ways. Most importantly, this is the first systematic study on CFs (for a review of the current state in the literature, see Meyer et al., 2021). We examine the impact of CFs on startups in various ways in primary and secondary markets for tokens, as well as the performance, performance persistence, and network effects of CFs. CFs are a new intermediary in entrepreneurial finance that exploit the fact that tokens are legally classified as "non-securities," which exempts CFs from most regulations that more traditional funds, such as equity-based venture capital (VC) funds, are subject to. Our results contribute to the literature on new players in entrepreneurial finance (for a review, see Block et al., 2018) by showing that CFs have emerged plausibly as a response to several threats to ICO market survival, such as asymmetric information problems like moral hazard (Momtaz, 2021b) and fraud (Hornuf et al., 2022), search and participation costs (Momtaz, 2022), and lack of disclosure requirements (Blaseg, 2018) and regulatory frameworks (Bellavitis et al., 2021). CFs certify project legitimacy (Fisch and Momtaz, 2020; Hsu, 2004) and provide networking-related services (Vismara, 2016), which plausibly improves the signaling efficiency in the ICO market (Vismara, 2018). Therefore, CFs are interesting to study and pave the way for promising avenues for future research (see Section 5.3) because they differ from more traditional intermediaries in numerous ways, e.g., by employing different investment strategies such as like hedge fund-style, quantitative strategies.

Another contribution of our study is that it provides evidence on the post-funding performance of startups and the valuation effects in secondary markets. Böckel et al. (2021, p. 433) summarize that there is a "research gap related to the post-funding phase" in the crowdfunding literature. Our study aims to fill this void by analyzing both the post-funding performance of startups and the valuation effects to CF backing announcements post-funding. Specifically, our study extends that by Fisch and Momtaz (2020), who only examine institutional investor-backed startups' BHARs for the six-month period post-ICO. We examine BHARs for various investment horizons of up to 24 months, and also exploit the cross-section of CFs by studying the various effects of CFs' investment strategies and scope on startups' post-funding performance. Similarly, no prior study has examined the announcement-related valuation effects on institutional investments in startups in public and liquid, secondary markets for tokens thus far, which is a novelty of our study. Because tokenized startups are traded in mostly liquid markets, information disclosures, such as CF backing announcements, entail short-term valuation effects on the token price. As such, we pave the way for more event studies in entrepreneurial finance and expect a growing literature on how public secondary markets for startups are shaped by news and related events much like the vast literature on event studies in corporate finance (MacKinlay, 1997).

Finally, our study contributes to the evolving ICO literature (Adhami et al., 2018; Adhami and Guegan, 2020; Belitski and Boreiko, 2021; Bellavitis et al., 2020; Bellavitis et al., 2021; Benedetti and Kostovetsky, 2021; Block et al., 2021; Bollaert et al., 2021; Boreiko and Risteski, 2021; Chen and Bellavitis, 2020; Colombo et al., 2021; Fisch, 2019; Fisch et al., 2021; Fisch et al., 2022; Giudici and Adhami, 2019; Giudici et al., 2020; Howell et al., 2020; Huang et al., 2020; Lyandres et al., 2022; Momtaz, 2020, 2021a, 2021b, 2021c), and in particular on ICO investors (Boreiko and Risteski, 2021; Fahlenbrach and Frattaroli, 2021) and intermediaries (Boreiko and Vidusso, 2019; Fisch and Momtaz, 2020; Momtaz, 2022), by examining the success of ICO firms in primary and secondary markets for tokens, as well as how it is affected by CFs.

Additionally, our study has practical implications for entrepreneurs, investors, and policymakers. First, for entrepreneurs, securing CF backing is always associated with positive rents, no matter whether it is during the primary market or in the secondary market for tokens. However, the optimal investment strategy and scope differ for primary and secondary markets. In the primary market, entrepreneurs are well-advised to seek backing from venture-style and diversified CFs, while endorsement from hedge fund-style and specialized CFs pays off more in the secondary market. Second, for individual investors, investing in CF-backed startups is associated with higher returns. For institutional investors such as CFs, the disclosure of investments must be timed well to benefit from announcement returns. Third, for policymakers, our findings suggest that the market for tokens may become increasingly efficient even without regulation because intermediaries, such as CFs, enter the market and extract rents by reducing costly frictions. Nevertheless, because CFs largely trade in non-securities and are thus exempt from most regulations concerning traditional funds, policymakers have to adapt existing securities laws to include tokens, paying attention to the intricacies of the rapidly growing market for tokens.

5.3 Limitations and Avenues for Future Research

Our study represents the first empirical work on CFs and their impact on startups. Given the rapidly growing presence of CFs in entrepreneurial finance, as illustrated in Figure 1, it seems very likely that a vivid literature around CFs and their role in entrepreneurial finance markets, and especially for token-based crowdfunding, will soon emerge. In the following, we thus offer some avenues for potentially fruitful future research.

Understanding the mechanisms behind CFs' impact on tokenized startups. Our study focuses on the valuation and post-funding performance of CF-backed startups, as well as the announcement returns of CF backing in the secondary market for tokens. Therefore, one potential limitation of our study is its focus on the financial effects of CF backing, which leaves room for future research on the non-financial effects, such as impact of CF involvement on startups' operating performance. Similarly, our results suggest that CF backing has a positive effect on startups that is driven by the investor network. While information asymmetry seems to play a role, little is known, however, about why and how exactly the investor network matters. Further, public markets for tokenized startups have enabled new features in entrepreneurial finance, e.g., the possibility to buy into and exit a startup investment *anytime* in liquid secondary markets, which have important implications. For instance, it would be worthwhile to disentangle the positive effects, e.g., coaching and operational guidance, from the negative effects, e.g., information disclosure and investor relation costs, of CF backing in secondary markets for tokenized startups. Or phrased as a question, can public markets for tokenized startups — with their permanent threats of takeover or exit — reinforce entrepreneurial discipline (similar to the market for corporate control (Jensen and Ruback, 1983)), or do they lead to unhealthy levels of short-termist pressure, leading to entrepreneurial myopia and harming aggregate entrepreneurship in the economy?

Intermediation in markets for tokenized startups in the long run. Our results suggest that CFs and CF-backed startups earn economic rents because the market for tokens is relatively inefficient. CFs have the resources and skills to partially overcome some of the frictions in the market for tokens, which yields economic surplus (Fisch and Momtaz, 2020; Momtaz, 2022). However, as the market matures, it will become more efficient. For example, participation and search costs will decrease as investors learn about blockchain- and smart contract-specific risks, and other market frictions will reduce as more market-wide institutions form, e.g., regulatory frameworks and disclosure standards (Bellavitis et al., 2021; Blaseg, 2018). Whether CFs will continue to beat the market as it becomes more efficient is questionable, however, and represents an interesting avenue for future research. It is a well-known fact that mutual funds are not able to outperform the market (Berk and Green, 2004; Sharpe, 1991), which is the natural benchmark to which CF performance may plausibly subside in the long term. Moreover, our findings on CF outperformance are based on a simple CAPM-like risk adjustment. The question of the correct risk adjustment is controversial in finance and, in particular, in entrepreneurial finance (Cochrane, 2005) and cryptocurrencies (Li and Yi, 2019). Therefore, whether investors in tokenized startups and CFs earn a financial return that is commensurate to the risk they take deserves more attention in future research.

5.4 Concluding Remarks

This study has sought to shed light on the role of crypto funds (CFs) in token-based entrepreneurial finance markets. CFs are a novel intermediaries that combine venture- with hedge fund-style investment strategies, exploiting the fact that tokenized startups can be traded in public secondary markets for tokens. CF-backed startups achieve higher valuations, perform better in the long term, and benefit from short-term announcement returns associated with CF investment disclosure in secondary markets for tokens. Similarly, CFs are able to beat the overall token market. Their outperformance is even persistent in subsequent periods, suggesting that their outperformance is skill-driven. The positive effects for startups and CFs are increasing in CFs' investor network centrality. Overall, this study paves the way for future research on the "crypto fund revolution" (Mokhtarian and Lindgren, 2018) in entrepreneurial finance.

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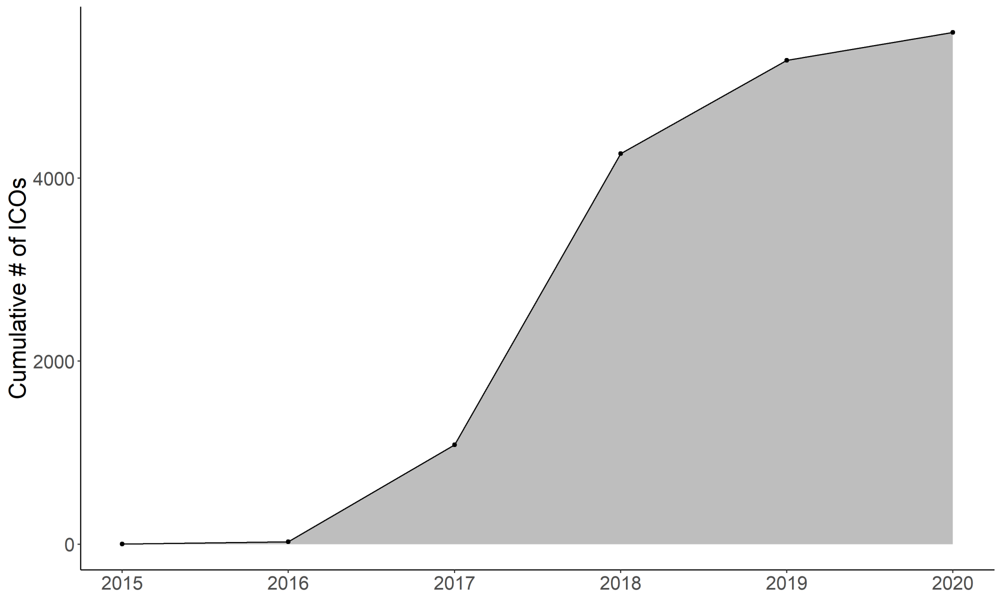
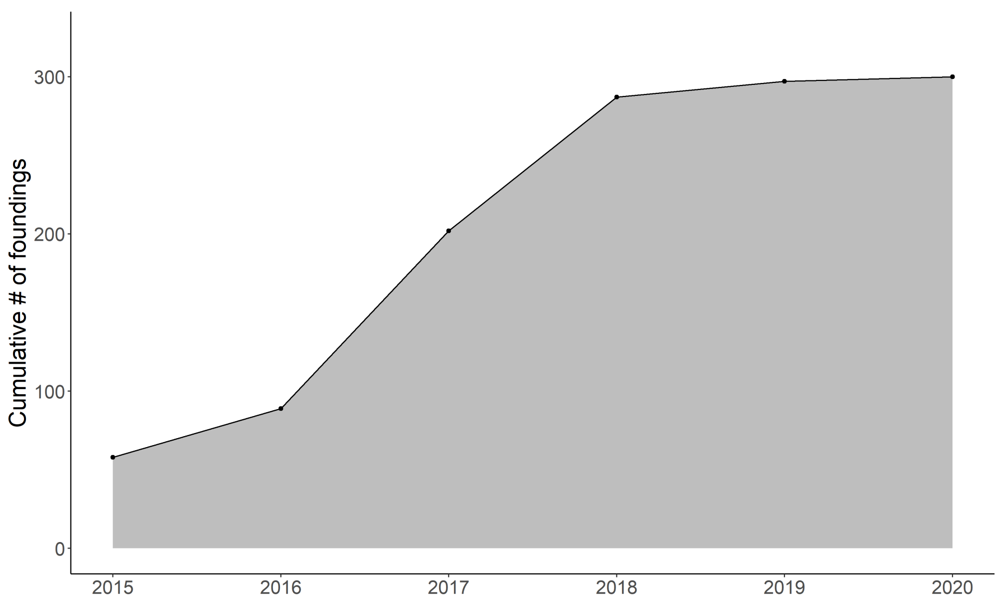
Figures

Figure 1: **The Evolution of the ICO Market and Crypto Funds**

Panel A: The Evolution of the ICO Market



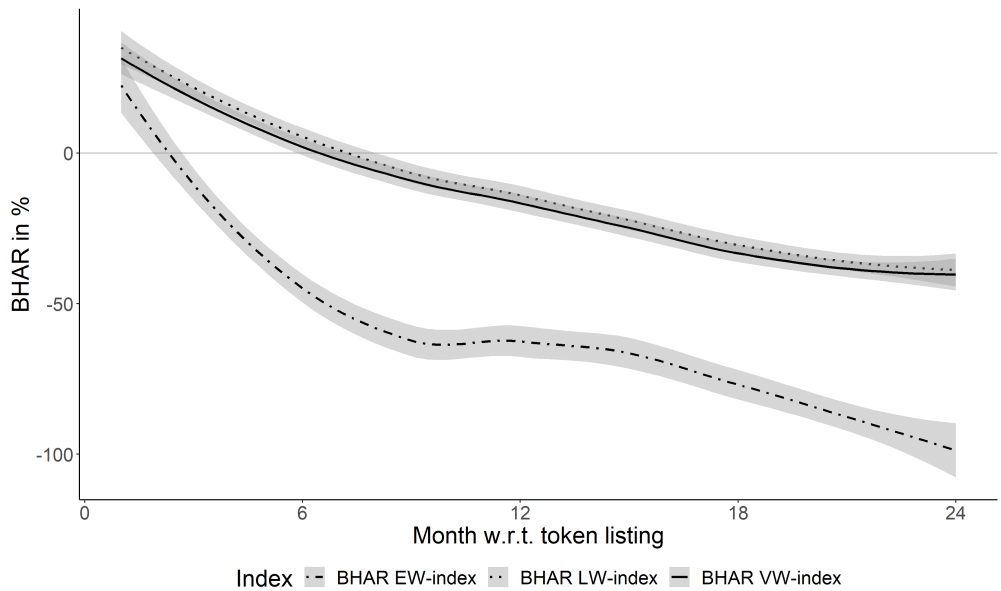
Panel B: The Evolution of Crypto Funds



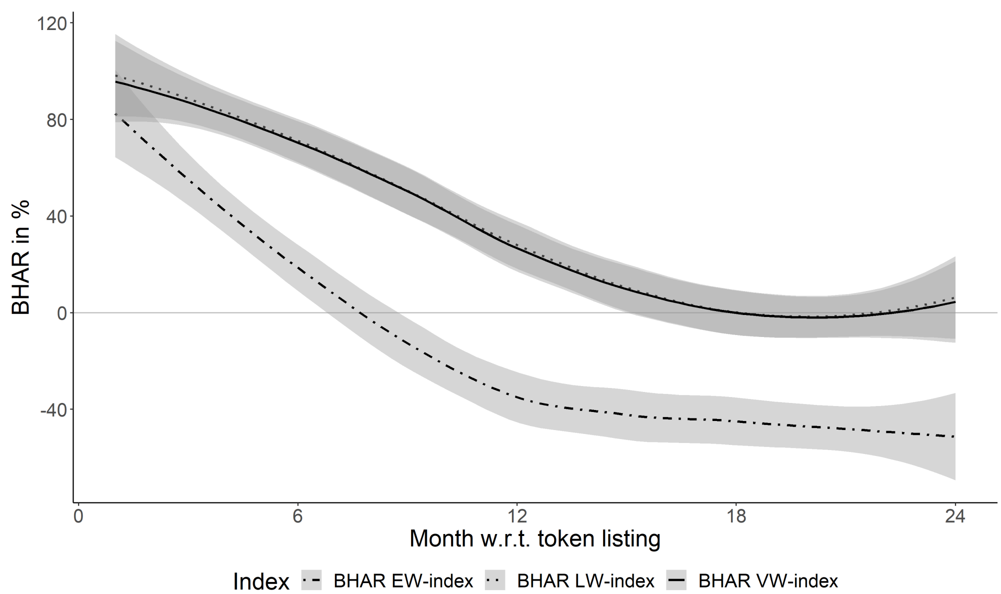
Note: Panel A depicts the cumulative number of ICOs from 2015 until September 2020. Our sample contains 5,592 ICOs with information on the ICO date. Panel B displays the cumulative number of crypto fund foundings during the same period. In total, 300 CFs in our sample list a founding year.

Figure 2: **Buy-and-Hold Abnormal Returns for Startup Firms**

Panel A: For all Startup Firms

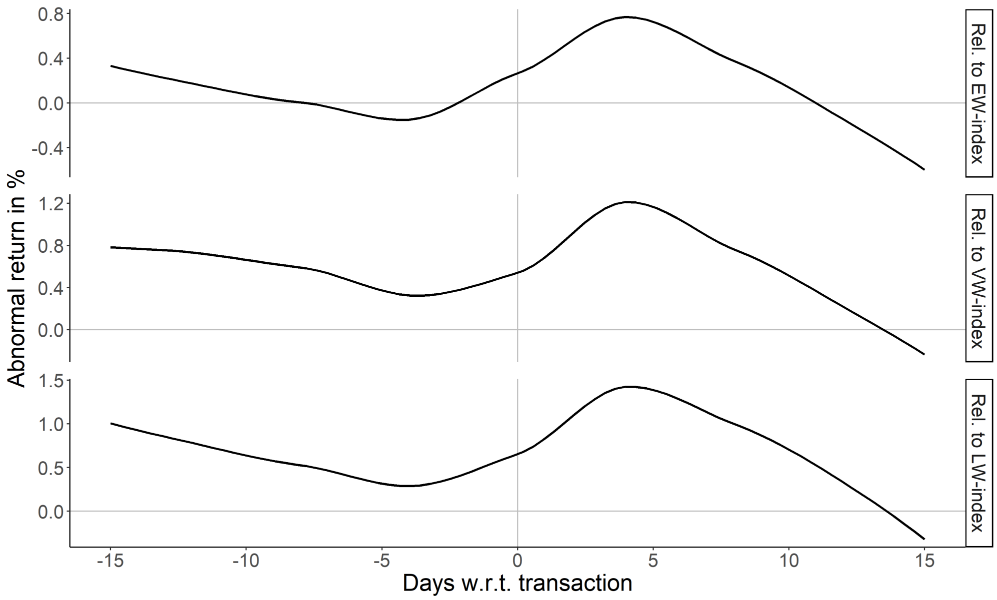


Panel B: For Startup Firms with CF backing



Note: This figure illustrates mean buy-and-hold abnormal returns (BHARs) for startup firms, following a token exchange listing. Panel A shows the results for all startup firms (with and without CF backing), whereas Panel B focuses on startup firms with CF backing. BHARs are reported over holding periods from 1 to 24 months relative to an equally-weighted (EW), liquidity-weighted (LW), and value-weighted (VW) market benchmark. The lines depict smoothed BHARs using locally estimated scatterplot smoothing together with confidence intervals.

Figure 3: **Post-ICO Crypto Fund Announcement Returns in the Secondary Market**



Note: This figure shows daily mean abnormal token returns associated with the post-ICO announcement of a CF investment in the secondary market. Abnormal returns, relative to equally-weighted (EW), value-weighted (VW), and liquidity-weighted (LW) token market benchmarks, are presented for the [–15,+15] event window, with $t = 0$ as the identified announcement date. Returns are in % per day. The lines depict smoothed abnormal returns using locally estimated scatterplot smoothing.

Tables

Table 1: **Blockchain-based Crowdfunding Performance: Summary Statistics**

Panel A: All Startups			
	Mean	*SD*	*Median*
Funding Success:			
Funding amount, in $ (log.)	14.951	2.002	15.224
Post-funding Performance:			
6-month buy-and-hold abnormal return (BHAR), in %	6.33	260.38	–43.02
12-month BHAR, in %	–17.70	217.72	–63.75
18-month BHAR, in %	–34.78	170.37	–54.82
24-month BHAR, in %	–40.77	145.00	–51.76
Announcement Return for CF Backings in Aftermarket:			
Cumulative abnormal return (CAR), [–5,+5], in %	4.38	31.56	–3.00

Panel B: CF- vs. Non-CF-backed Startups			
	Mean CF-backed	*Mean Non-CF-backed*	*Δ in Means: CF – Non-CF*
Funding Success:			
Funding amount, in $ (log.)	16.365	14.711	1.655***
Post-funding Performance:			
6-month buy-and-hold abnormal return (BHAR), in %	90.94	–20.17	111.10***
12-month BHAR, in %	23.03	–32.84	55.86***
18-month BHAR, in %	–3.28	–47.45	44.17***
24-month BHAR, in %	–4.25	–57.54	53.29***
Announcement Return for CF Backings in Aftermarket:			
Cumulative abnormal return (CAR), [–5,+5], in %	4.82	2.83	1.99

Panel C: All Crypto Funds			
	Mean	*SD*	*Median*
Risk-adjusted Performance:			
CAPM-alpha, monthly, in %	2.69	25.26	3.34
Sharpe ratio, monthly	0.12	0.12	0.03
Performance Persistence:			
Performance persistence CAPM-alpha	1.028	0.436	1

Note: This table reports summary statistics for our outcome variables of all startups and crypto funds in Panel A and C, respectively. Panel B compares the performance between CF-backed and non-CF-backed startups. CF performance persistence is measured as the fraction of positive CAPM-alphas in year two vis-à-vis year one (see Section 3.2.2 for details). All performance measures are computed using a value-weighted token market benchmark. The results are similar for equally-weighted and liquidity-weighted benchmark adjustments. All variables are defined in Table A1. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 2: **Crypto Fund Characteristics and Control Variables: Summary Statistics**

	Mean	**SD**	**Q1**	**Median**	**Q3**
Crypto Funds (CFs):					
Startups with CF backing, in %	6.19	24.10	0	0	0
CF Investment Strategy:					
Venture-style capital, in %	5.12	22.04	0	0	0
Hedge fund-style capital, in %	2.32	15.05	0	0	0
CF Investment Scope:					
Specialization, in %	2.24	14.80	0	0	0
Diversification, in %	4.93	21.66	0	0	0
Firm characteristics:					
Expert rating	2.921	0.764	2.4	2.9	3.5
GitHub open-sourced	0.509	0.500	0	1	1
Business model: Platform	0.482	0.500	0	0	1
# targeted industries	2.900	2.397	1	2	4
Ethereum blockchain	0.872	0.334	1	1	1
Offering characteristics:					
Pre-sale	0.493	0.500	0	0	1
Promotion scheme: Bonus	0.066	0.249	0	0	0
Promotion scheme: Reward	0.264	0.441	0	0	1
KYC	0.416	0.493	0	0	1
# competing ICOs	771	525	395	723	1,005
Market characteristics:					
Bull market	0.210	0.407	0	0	0
Bear market	0.524	0.499	0	1	1
Sideways market	0.249	0.432	0	0	0
Market volatility during ICO, value-weighted	0.116	0.054	0.084	0.109	0.146
Human capital characteristics:					
# team members	10.738	7.268	5	9	15
# team members with technical degree	2.935	2.887	1	2	4
# team members with Ph.D.	0.584	1.051	0	0	1
# team members with crypto experience	4.301	3.635	2	3	6
Network-related social capital:					
CF investor network centrality	97	57	57	97	128
Startup firm network centrality	28	40	7	14	30

Note: This table reports summary statistics on CF backing and control variables for our aggregate startup sample. All variables are defined in Table A1.

Table 3: **The Impact of Crypto Funds on Firm Valuations: A Two-Stage Analysis**

	1st stage		2nd stage		
Model:	**OLS**	**Selection**	**IMR**	**PSM**	**IV**
Dependent variable:	Valuation	$\mathbb{1}_{\text{Crypto Fund}}$	Valuation	Valuation	Valuation
	(1)	(2)	(3)	(4)	(5)
Crypto Fund	1.004***		0.942***	0.960***	1.047***
	(0.132)		(0.135)	(0.132)	(0.145)
Firm characteristics:					
Expert rating	0.412***	0.189*	0.366***	0.380***	0.413
	(0.095)	(0.111)	(0.097)	(0.104)	(0.420)
GitHub open-sourced	–0.222**	0.008	–0.219**	–0.154	–0.762
	(0.104)	(0.118)	(0.104)	(0.113)	(0.546)
Business model: Platform	–0.001	0.258**	–0.057	0.039	–0.609
	(0.103)	(0.117)	(0.106)	(0.114)	(0.441)
# targeted industries	–0.050**	0.006	–0.049**	–0.076***	–0.004
	(0.023)	(0.033)	(0.023)	(0.026)	(0.062)
Ethereum blockchain	–0.027	–0.016	–0.017	–0.205	0.692
	(0.157)	(0.175)	(0.157)	(0.177)	(0.733)
Offering characteristics:					
Pre-sale	–0.069	–0.438***	0.038	–0.117	0.274
	(0.102)	(0.112)	(0.112)	(0.110)	(0.461)
Promotion scheme: Bonus	0.808	0.337	0.643	0.808	–1.191
	(0.643)	(0.674)	(0.646)	(0.635)	(3.165)
Promotion scheme: Reward	–0.081	–0.360***	–0.007	–0.049	–0.905**
	(0.111)	(0.139)	(0.116)	(0.127)	(0.421)
KYC	0.167	–0.001	0.172	0.097	1.027**
	(0.119)	(0.138)	(0.119)	(0.133)	(0.459)
# competing ICOs	0.0001	–0.001*	0.0002	–0.0002	–0.001*
	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.001)
Market characteristics:					
Bull market	0.123	–0.133	0.159	0.003	1.162**
	(0.207)	(0.256)	(0.207)	(0.224)	(0.538)
Bear market	0.148	–0.303	0.181	0.031	1.093*
	(0.222)	(0.298)	(0.222)	(0.255)	(0.574)
Market volatility during ICO, value-weighted	0.257	–1.942*	0.904	0.579	4.743
	(0.981)	(1.038)	(1.021)	(1.042)	(4.514)
Human capital characteristics:					
# team members	0.034***	–0.016	0.039***	0.031***	0.002
	(0.009)	(0.011)	(0.009)	(0.010)	(0.052)
# team members with technical degree	–0.027	0.070***	–0.048**	–0.018	0.079
	(0.020)	(0.022)	(0.022)	(0.022)	(0.084)
# team members with Ph.D.	0.011	0.136***	–0.029	0.019	–0.227
	(0.043)	(0.039)	(0.047)	(0.046)	(0.234)
# team members with crypto experience	0.018	0.007	0.017	0.011	0.055
	(0.016)	(0.017)	(0.016)	(0.017)	(0.076)
Inverse Mills Ratio (IMR)	✗	✗	✓	✗	✗
Propensity Score Matching (PSM)	✗	✗	✗	✓	✗
Instrumental Variable (IV)	✗	✗	✗	✗	✓
Country fixed effects	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓
Observations	1,226	1,226	1,226	950	1,226
Adjusted R^2	0.214	.	0.217	0.224	.
McFadden R^2	.	0.250	.	.	.
Wald test	.	.	.	.	9.30***

Note: This table presents two-stage regression results for the effect of CF backing on firm valuation (in $, log.). We control for a comprehensive set of control variables, including firm, offering, market, and human capital-related characteristics. Model (1) reports the results of the OLS regression. Model (2) shows the selection model, in which CF backing is a function of all control variables. Models (3), (4), and (5) are second-stage regressions that rely on Inverse Mills Ratios (IMR), propensity score matching (PSM), and instrumental variables (IV), respectively, to control for a potential selection bias. Details on the econometric approach are described in Section 3.6. For the IV model, the Wald test statistic reports the model fit. All models include country and quarter-year fixed effects. Robust standard errors are reported in parentheses. All variables are defined in Table A1. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 4: **Crypto Funds and Firm Valuations: The Impact of Investment Strategy and Scope**

	Panel A: Investment Strategy			*Panel B: Investment Scope*		
Stage:	1st	2nd	2nd	1st	2nd	2nd
Model:	OLS	IMR	IV	OLS	IMR	IV
Dependent variable:	Valuation	Valuation	Valuation	Valuation	Valuation	Valuation
	(1)	(2)	(3)	(4)	(5)	(6)
Investment strategy:						
Venture-style	0.883^{***}	0.809^{***}	0.860^{***}			
	(0.170)	(0.174)	(0.174)			
Hedge fund-style	0.478^{**}	0.416^{*}	0.434^{*}			
	(0.242)	(0.247)	(0.238)			
Investment scope:						
Specialization				0.439^{*}	0.428^{*}	–0.534
				(0.239)	(0.247)	(0.887)
Diversification				0.955^{***}	0.890^{***}	1.413^{***}
				(0.162)	(0.164)	(0.408)
Inverse Mills Ratio (IMR)	✗	✓	✗	✗	✓	✗
Instrumental Variable (IV)	✗	✗	✓	✗	✗	✓
Firm controls	✓	✓	✓	✓	✓	✓
Offering controls	✓	✓	✓	✓	✓	✓
Market controls	✓	✓	✓	✓	✓	✓
Human capital controls	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓	✓
Observations	1,226	1,226	1,226	1,226	1,226	1,226
Adjusted R^2	0.212	0.216	.	0.212	0.214	.
Wald Test	.	.	8.32^{***}	.	.	8.42^{***}

Note: This table tests whether the positive effect of CF backing on firm valuation in Table 3 is sensitive to CFs' investment strategy (venture- vs. hedge fund-style) and investment scope (specialization vs. diversification). Firm valuation (in \$, log.) is regressed on dummy variables for investment strategy and investment scope, replacing the CF indicator. Apart from this, the models and control variables correspond to those in Table 3. Panel A and B show the OLS, IMR, and IV models for investment strategy and investment scope, respectively. Details on the econometric approach are described in Section 3.6. For the IV model, the Wald test statistic reports the model's explanatory power. Since the estimated coefficients of the control variables are stable compared to the results in Table 3, we suppress them for brevity. All models include country and quarter-year fixed effects. Robust standard errors are reported in parentheses. All variables are defined in Table A1. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 5: **Difference in BHARs between CF-backed vs. Non-CF-backed Startups**

	Δ (*∅ CF – ∅ Non-CF*)			Δ (*Median CF – Median Non-CF*)		
	$BHAR_{VW}$ (1)	$BHAR_{EW}$ (2)	$BHAR_{LW}$ (3)	$BHAR_{VW}$ (4)	$BHAR_{EW}$ (5)	$BHAR_{LW}$ (6)
6 months	111.10***	109.41***	100.60***	19.39***	31.26***	17.97***
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
12 months	55.86***	34.84*	56.05***	44.76***	35.22***	43.04***
(p-value)	(0.002)	(0.09)	(0.002)	(0.00)	(0.00)	(0.00)
18 months	44.17***	46.54***	40.35***	12.32***	18.72***	11.64***
(p-value)	(0.01)	(0.002)	(0.01)	(0.00)	(0.00)	(0.00)
24 months	53.29***	69.30***	55.18***	5.93***	20.65***	5.76***
(p-value)	(0.002)	(0.00)	(0.001)	(0.003)	(0.00)	(0.001)

Note: This table reports the performance differential of startups with and without CF backing. Buy-and-hold abnormal returns (BHARs) are computed using value-weighted (VW), equally-weighted (EW), and liquidity-weighted token (LW) market benchmarks. Results are presented for differences in means (columns (1) – (3)) and medians (columns (4) – (6)) over four holding periods (6, 12, 18, and 24 months). BHAR differentials are in % over the respective holding period. *, **, and *** show statistical difference from zero at the 0.10, 0.05, and 0.01 level, respectively, and are based on t-tests for means and Wilcoxon-tests for medians.

Table 6: **The Impact of Crypto Funds on Startups' Post-Funding Performance**

	1st stage		2nd stage		
Model:	**OLS**	**Selection**	**IMR**	**PSM**	**IV**
Dependent variable:	24-mo BHAR	$\mathbb{1}_{\text{Crypto Fund}}$	24-mo BHAR	24-mo BHAR	24-mo BHAR
	(1)	(2)	(3)	(4)	(5)
Crypto Fund	0.178**		0.166**	0.179**	0.251**
	(0.076)		(0.077)	(0.078)	(0.109)
Firm characteristics:					
Expert rating	0.140*	0.051	0.134*	0.157**	0.504
	(0.072)	(0.161)	(0.072)	(0.075)	(0.539)
GitHub open-sourced	–0.020	0.0004	–0.016	–0.009	–0.412
	(0.075)	(0.180)	(0.075)	(0.078)	(0.491)
Business model: Platform	–0.010	0.043	–0.017	–0.008	0.043
	(0.076)	(0.172)	(0.077)	(0.080)	(0.371)
# targeted industries	0.010	0.057	–0.004	0.002	0.004
	(0.021)	(0.054)	(0.025)	(0.022)	(0.090)
Ethereum blockchain	0.142	–0.348	0.240	0.119	–0.022
	(0.132)	(0.281)	(0.171)	(0.139)	(0.471)
Offering characteristics:					
Pre-sale	–0.040	–0.262	0.017	–0.047	0.147
	(0.076)	(0.179)	(0.098)	(0.080)	(0.346)
Promotion scheme: Bonus	0.0003	0.268	–0.090	–0.006	–0.691
	(0.245)	(0.524)	(0.265)	(0.250)	(0.942)
Promotion scheme: Reward	0.051	–0.732**	0.199	0.064	–0.303
	(0.105)	(0.297)	(0.195)	(0.115)	(0.318)
KYC	0.072	0.217	0.031	0.101	–0.195
	(0.098)	(0.245)	(0.108)	(0.106)	(0.276)
# competing ICOs	–0.00001	–0.001	0.0001	0.00005	–0.0002
	(0.0002)	(0.001)	(0.0002)	(0.0002)	(0.0004)
Market characteristics:					
Bull market	0.010	0.281	–0.061	0.0001	0.143
	(0.146)	(0.341)	(0.166)	(0.155)	(0.478)
Bear market	–0.063	–0.044	–0.066	–0.094	–0.186
	(0.164)	(0.397)	(0.164)	(0.172)	(0.455)
Market volatility during ICO, value-weighted	0.363	–1.522	0.723	0.431	0.882
	(0.654)	(1.645)	(0.768)	(0.691)	(3.049)
Human capital characteristics:					
# team members	–0.016**	–0.021	–0.010	–0.018***	0.035
	(0.007)	(0.015)	(0.009)	(0.007)	(0.022)
# team members with technical degree	0.011	0.039	0.002	0.013	–0.018
	(0.015)	(0.035)	(0.018)	(0.016)	(0.042)
# team members with Ph.D.	0.017	0.032	0.008	0.024	0.034
	(0.032)	(0.070)	(0.033)	(0.034)	(0.135)
# team members with crypto experience	0.012	0.009	0.009	0.012	–0.071
	(0.013)	(0.028)	(0.013)	(0.013)	(0.079)
Inverse Mills Ratio (IMR)	✗	✗	✓	✗	✗
Propensity Score Matching (PSM)	✗	✗	✗	✓	✗
Instrumental Variable (IV)	✗	✗	✗	✗	✓
Country fixed effects	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓
Observations	361	361	361	318	361
Adjusted R^2	0.455	.	0.455	0.480	.
McFadden R^2	.	0.211	.	.	.
Wald test	.	.	.	.	1.7**

Note: This table presents two-stage regression results for the effect of CF backing on 24-month BHAR. The models and confounding factors are identical to those in Table 3. Only the dependent variable is replaced in models (1), (3), (4), and (5). Model (1) reports the OLS regression, model (2) the selection mechanism. Models (3), (4), and (5) are second-stage regressions based on Inverse Mills Ratios (IMR), propensity score matching (PSM), and instrumental variables (IV). Details on the econometric approach are described in Section 3.6. For the IV model, the Wald test statistic reports the model fit. All models include country and quarter-year fixed effects. Robust standard errors are reported in parentheses. All variables are defined in Table A1. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 7: **Crypto Funds and Post-Funding Token Price Performance: The Impact of Investment Strategy and Scope**

	Panel A: Investment Strategy			*Panel B: Investment Scope*		
Stage:	1st	2nd	2nd	1st	2nd	2nd
Model:	OLS	IMR	IV	OLS	IMR	IV
Dependent variable:	24-mo BHAR	24-mo BHAR	24-mo BHAR	24-mo BHAR	24-mo BHAR	24-mo BHAR
	(1)	(2)	(3)	(4)	(5)	(6)
Investment strategy:						
Venture-style	0.031	0.015	0.065			
	(0.095)	(0.097)	(0.151)			
Hedge fund-style	0.268**	0.269**	0.432*			
	(0.134)	(0.136)	(0.261)			
Investment scope:						
Specialization				0.305**	0.315**	0.146
				(0.134)	(0.140)	(0.561)
Diversification				0.073	0.064	0.209
				(0.089)	(0.091)	(0.247)
Inverse Mills Ratio (IMR)	✗	✓	✗	✗	✓	✗
Instrumental Variable (IV)	✗	✗	✓	✗	✗	✓
Firm controls	✓	✓	✓	✓	✓	✓
Offering controls	✓	✓	✓	✓	✓	✓
Market controls	✓	✓	✓	✓	✓	✓
Human capital controls	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓	✓
Observations	361	361	361	361	361	361
Adjusted R^2	0.455	0.452	.	0.459	0.456	.
Wald Test	.	.	1.84**	.	.	1.52*

Note: This table tests whether the positive effect of CF backing on post-funding performance in Table 6 varies by CFs' investment strategy (venture- vs. hedge fund-style) and investment scope (specialization vs. diversification). 24-month BHAR is regressed on dummy variables for investment strategy and investment scope, replacing the CF indicator. Expect the change in dependent variable, the models and confounding factors are analogous to those in Table 4. Panel A and B show the OLS, IMR, and IV models for investment strategy and investment scope, respectively. Details on the econometric approach are described in Section 3.6. For the IV model, the Wald test statistic reports the model's explanatory power. The coefficients of the control variables are similar to the results of Table 6 and are therefore suppressed for brevity. All models include country and quarter-year fixed effects. Robust standard errors are reported in parentheses. All variables are defined in Table A1. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 8: **Post-ICO Crypto Fund Announcement Returns in the Secondary Market**

	Pre-announcement Daily ∅ AR [–5,–1]		**Post-announcement** Daily ∅ AR [0,+5]		**Difference** Δ AR [0,+5] – AR [–5,–1]	
Value-weighted, in %	0.00	(p-val.=1.00)	1.37**	(0.02)	1.37*	(0.08)
Equally-weighted, in %	–0.45	(0.34)	1.00*	(0.10)	1.45*	(0.06)
Liquidity-weighted, in %	–0.00	(1.00)	1.50**	(0.01)	1.50*	(0.05)

Note: This table presents daily mean abnormal token returns (AR) associated with the post-ICO announcement of a CF investment in the secondary market. Results are shown for the [–5,–1] pre-announcement and [0,+5] post-announcement periods as well as their return differential. ARs are computed using value-weighted, equally-weighted, and liquidity-weighted token market benchmarks. Returns are in % per day. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Table 9: **Characteristics and Performance of Crypto Funds**

Panel A: Summary Statistics for Crypto Fund Characteristics						
	Mean	**SD**	**Q1**	**Median**	**Q3**	**N**
Venture-style capital, share in %	52.66	50.00	0	100	100	338
Hedge fund-style capital, share in %	47.34	50.00	0	0	100	338
Specialization, share in %	52.53	50.00	0	100	100	257
Diversification, share in %	47.47	50.00	0	0	100	257
# of investments	16.47	13.01	6	14	20	257
AuM, in $M	96.88	147.89	15	40	90.75	160
# of staff	8.31	10.29	3	5	8	306
Fund age, in years	3.77	2.11	2.25	3.25	4.25	300
Performance incentive	11.59	4.54	10	10	10.45	59
# team members with crypto experience	0.33	0.58	0	0	1	269
# team members with invest. experience	0.32	0.54	0	0	1	269
# team members with Ph.D.	0.14	0.39	0	0	0	253
CF investor network centrality	127	69	71	126	184	299

Panel B: Crypto Funds' Risk-adjusted Performance (# fund-month obs. = 11,055)						
	CAPM-alpha, monthly, in %			**Sharpe ratio, monthly**		
	VW	EW	LW	VW	EW	LW
Mean	2.69***	2.52***	2.71***	0.12***	0.12***	0.12***
SD	25.26	25.12	25.21	0.12	0.12	0.12
Q1	0.79	0.73	0.87	0.03	0.04	0.04
Median	3.34***	2.74***	2.99***	0.13***	0.12***	0.13***
Q3	5.01	4.64	4.83	0.21	0.18	0.21
Skewness	–0.54	–0.65	–0.57	0.24	0.48	0.22
Kurtosis	4.46	4.26	5.00	6.28	7.34	6.93

Note: This table reports summary statistics for CF characteristics (Panel A) and their risk-adjusted performance (Panel B). Performance is measured relative to a value-weighted, equally-weighted, and liquidity-weighted token market index. All variables are defined in Table A1. Returns are in % per month. *, **, and *** show statistical difference from zero at the 0.10, 0.05, and 0.01 level, respectively, and are based on t-tests for means and Wilcoxon-tests for medians.

Table 10: **Crypto Fund Performance Persistence: A Test of Skill vs. Luck**

Dependent variables: Share of positive alphas in CFs' subsequent lifetime				
	$\sum_{\substack{\text{Month}\in\\\{7,18\}}} \mathbb{1}[\alpha>0]/12$		$\sum_{\substack{\text{Month}\in\\\{13,24\}}} \mathbb{1}[\alpha>0]/12$	
	(1)	(2)	(3)	(4)
Independent variables:				
Share of positive alphas in CFs' start period:				
$\sum_{\substack{\text{Month}\in\\\{1,6\}}} \mathbb{1}[\alpha>0]/6$	0.320***	0.097*		
	(0.042)	(0.058)		
$\sum_{\substack{\text{Month}\in\\\{1,12\}}} \mathbb{1}[\alpha>0]/12$			0.463***	0.180**
			(0.053)	(0.080)
Fund-level controls	✗	✓	✗	✓
Fund-level human capital controls	✗	✓	✗	✓
Quarter-year fixed effects	✓	✓	✓	✓
Observations	339	165	321	157
Adjusted R^2	0.327	0.406	0.358	0.428

Note: This table tests whether CF outperformance is persistent. Following Nanda et al. (2020), the fraction of months with positive alphas in one period is regressed on the same fraction in a preceding period, controlling for a set of variables. Columns (1) and (2) test how the fraction in the first six investment months affects the fraction over the following twelve months, whereas columns (3) and (4) test for the influence of the first year on the second year. Results are shown for CAPM-alphas measured using a value-weighted token market benchmark. All models include quarter-year fixed effects. Columns (2) and (4) add fund-level and human capital characteristics as control variables, which are suppressed for brevity. The results remain unchanged when using equally- and liquidity-weighted benchmarks. Heteroskedasticity-adjusted standard errors are reported in parentheses. $^{*}p<.10$; $^{**}p<.05$; $^{***}p<.01$.

Table 11: **Startup and Crypto Fund Performance: The Role of the Investor Network**

	Panel A: Startup performance			*Panel B: CF performance (persistence)*		
Dependent variables:	Valuation	BHAR	CAR	CAPM-α	SR	$\sum_{\substack{\text{Month}\in\\ \{13,24\}}} \mathbb{1}[\alpha > 0]/12$
	(1)	(2)	(3)	(4)	(5)	(6)
CF investor network centrality	0.004*	0.012**	0.005**	0.020***	0.083***	0.038*
	(0.002)	(0.005)	(0.002)	(0.008)	(0.027)	(0.021)
Startup firm network centrality	–0.010	0.018	0.013			
	(0.006)	(0.018)	(0.010)			
CF investor network $\times$ Startup firm network	0.006	–0.022	–0.022*			
	(0.005)	(0.015)	(0.011)			
Fund-level controls	✗	✗	✗	✓	✓	✓
Fund-level human capital controls	✗	✗	✗	✓	✓	✓
Fund-level initial performance control	✗	✗	✗	✗	✗	✓
Offering controls	✓	✓	✗	✗	✗	✗
Market controls	✓	✓	✗	✗	✗	✗
Country fixed effects	✓	✓	✗	✗	✗	✗
Quarter-year fixed effects	✓	✓	✗	✗	✗	✓
Observations	190	112	24	162	162	154
Adjusted R^2	0.357	0.214	0.213	0.070	0.070	0.432

Note: This table presents regression results for the effect of the investor network on startup and CF performance measures in Panel A and B, respectively. For startup performance, we assess the effect on firm valuation (in $, log.), 24-month BHAR, and the CAR over the [–5, +5] event window. For CF performance, our dependent variables are monthly CAPM-alpha, Sharpe ratio, and our performance persistence measure (here: the fraction of positive alphas in the second year of a fund's lifetime). Where applicable, performance measures are calculated using a value-weighted token market benchmark. The results are robust when risk-adjustments are derived with equally- and liquidity-weighted benchmarks. Depending on the performance measure, we control for a varying set of confounding factors, including fund, fund-level human capital, fund-level initial performance (first year), token offering, and market characteristics as well as country and quarter-year fixed effects. For startup performance, we further control for the startup firm network and its interaction term to the investor network. The estimated coefficients on the control variables are suppressed for brevity. The coefficients of CF investor network centrality (in Panel B) and the interaction term between the CF investor network and the startup firm network (in Panel A) are multiplied by 100. Robust standard errors are reported in parentheses. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Appendix

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

Variable	Description	Data source
	Panel A: Performance measurement – Startups	
ICO firm valuation	ICO firm valuation measured as the natural logarithm of the total amount raised during the ICO (in $ million).	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
Cumulative abnormal return (CAR) around CF investment announcements in the aftermarket	The impact of CF investment announcements on short-term token price performance in public secondary markets over varying event windows, ranging from [–5, +5] to [–15, +15] in days, with t=0 as the announcement date. To compute CARs, token returns are adjusted for the market index's return over the same event window.	CoinMarketCap
	Panel B: Performance measurement – Crypto funds	
CAPM-alpha	Defined as a fund's average monthly return in excess of the expected return. The value-weighted token market index (VW-index) serves as our main benchmark.	Crypto Fund Research, CoinMarketCap
Sharpe ratio (SR)	Measured as a fund's alpha divided by the standard deviation of the fund's alpha. Reported are both the CAPM-alpha and the SR using value-, equally-, and liquidity-weighted market-risk adjustments.	Crypto Fund Research, CoinMarketCap
Performance persistence	Measured as the fraction of CF positive alphas in two consecutive time periods. For example, to compute the performance persistence in year two vis-à-vis year one, our proxy for managerial skill is defined as the share of positive alphas in year two divided by the share of positive alphas in year one.	Crypto Fund Research, CoinMarketCap
	Panel C: Independent variables	
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
Venture-style capital	Dummy variable equal to one if at least one invested CF has a venture-style investment strategy, and zero otherwise.[24]	Crypto Fund Research, investor websites
Hedge fund-style capital	Dummy variable equal to one if at least one invested CF has a hedge fund-style investment strategy, and zero otherwise.[24]	Crypto Fund Research, investor websites
Specialization	Dummy variable equal to one if at least one invested CF has a specialized investment scope, and zero otherwise. All funds are classified as either specialized or diversified based on the median number of investments of all funds (i.e., below median classifies a CF as a specialized fund).[24]	Crypto Fund Research, investor websites
Diversification	Dummy variable equal to one if at least one invested CF has a diversified investment scope, and zero otherwise.[24]	Crypto Fund Research, investor websites

[24] In the context of CF performance analysis: Dummy variable equal to one if the CF matches the respective investment strategy or scope, and zero otherwise.

CF investor network centrality	Defined as the number of a fund's connections to other CFs through their combined token investments. Following Bajo et al. (2020), we measure a fund's investor network centrality by using the number of first-degree connections to other CFs through investments in the same startups.	Crypto Fund Research, Crunchbase, investor and startup websites
Panel D: 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
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
Startup firm network centrality	Defined as the number of a firm's connections to other startups. Following Bajo et al. (2020), we first measure a network score for all team members via their first-degree connections to members of other firms (through working for these startups at the same time). To derive a network centrality score at the firm level, we take the average across all team members.	ICObench, ICOmarks
Panel E: 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 F: 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 G: Control variables – Human capital characteristics		
# team members	Number of team members of the firm.	ICObench
# team members with technical degree	Number of team members with a college degree in a technical field.	LinkedIn
# team members with Ph.D.	Number of team members with a Ph.D. degree.	LinkedIn

# team members with crypto experience	Number of team members with prior experience in blockchain technology.	LinkedIn
	Panel H: Control variables – Additional CF characteristics	
# of investments	Number of firms in which a crypto fund invested.	Crypto Fund Research, investor websites
AuM	Size of a CF measured by its assets under management (AuM, in $M million).	Crypto Fund Research, investor websites
# of staff	Size of a CF measured by its number of professional staff.	Crypto Fund Research, investor websites
Fund age	Time in the market of a CF since its founding, measured in years.	Crypto Fund Research, investor websites
Common law country	Dummy variable equal to one if the country's legal system of a CF's headquarter is classified as common law, and zero otherwise (zero indicates the legal system follows civil law logic; based on the classification by Zweigert and Kötz (1998)).	Crypto Fund Research, investor websites
Performance incentive	Performance incentive of CF managers measured by the ratio a fund's performance fee to its management fee.	Crypto Fund Research, investor websites
# team members with crypto experience	Number of team members with prior experience in blockchain technology.	LinkedIn
# team members with investment experience	Number of team members with prior investment experience.	LinkedIn
# team members with Ph.D.	Number of team members with a Ph.D. degree.	LinkedIn

Table A2: **Pairwise Correlations**

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. Funding amount, in $ (log.)															
2. 6-month BHAR, value-weighted	–0.01														
3. 12-month BHAR, value-weighted	–0.01	0.54													
4. 18-month BHAR, value-weighted	–0.02	0.41	0.71												
5. 24-month BHAR, value-weighted	0.07	0.41	0.68	0.73											
6. CAR, value-weighted [–5,+5]	0.13	0.04	0.42	0.04	0.18										
Fund characteristics															
7. Crypto Fund	0.29	0.18	0.11	0.12	0.17	0.03									
8. Venture-style capital	0.28	0.18	0.10	0.10	0.16	0.04	0.90								
9. Hedge-style capital	0.21	0.15	0.14	0.16	0.30	0.19	0.60	0.58							
10. Specialization	0.19	0.08	0.09	0.05	0.13	–0.002	0.59	0.61	0.65						
11. Diversification	0.28	0.17	0.13	0.13	0.18	0.06	0.89	0.94	0.65	0.53					
Firm characteristics															
12. Expert rating	0.16	–0.07	–0.04	–0.02	0.07	0.04	0.07	0.06	0.05	0.05	0.06				
13. GitHub open–sourced	0.01	–0.03	–0.003	0.03	–0.03	–0.08	0.04	0.05	0.04	0.04	0.04	0.44			
14. Business model: Platform	0.03	0.03	–0.04	–0.05	0.003	–0.09	0.04	0.04	0.03	0.04	0.04	0.14	0.09		
15. # targeted industries	–0.04	–0.09	–0.08	–0.10	–0.05	–0.20	–0.04	–0.04	–0.03	–0.02	–0.04	0.25	0.17	0.35	
16. Ethereum blockchain	0.04	0.01	–0.01	–0.10	–0.01	–0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.01	0.05	–0.01
Offering characteristics															
17. Pre-sale	–0.02	–0.12	–0.10	–0.14	–0.09	–0.03	–0.08	–0.09	–0.07	–0.05	–0.09	0.31	0.14	0.09	0.19
18. Promotion scheme: Bonus	0.0003	–0.05	0.02	–0.05	–0.03	–0.11	–0.04	–0.04	–0.03	–0.04	–0.04	0.08	0.04	0.06	0.08
19. Promotion scheme: Reward	–0.08	–0.09	–0.07	–0.06	–0.08	–0.18	–0.07	–0.07	–0.05	–0.05	–0.06	0.32	0.18	0.09	0.17
20. KYC	0.02	–0.12	–0.11	–0.15	–0.09	–0.12	–0.03	–0.03	–0.04	–0.02	–0.03	0.40	0.17	0.07	0.23
21. # competing ICOs	0.002	–0.17	–0.17	–0.24	–0.11	–0.26	–0.10	–0.11	–0.07	–0.05	–0.11	0.07	0.05	0.02	0.09
Market characteristics															
22. Bull market	0.08	0.16	0.14	0.18	0.14	0.23	0.14	0.12	0.09	0.06	0.12	–0.22	–0.08	0.01	–0.17
23. Bear market	0.06	–0.15	–0.16	–0.20	–0.14	–0.13	–0.03	–0.03	–0.03	–0.02	–0.03	0.16	0.09	0.03	0.13
24. Sideways market	–0.15	–0.01	0.004	–0.02		–0.30	–0.10	–0.08	–0.05	–0.05	–0.08	0.20	0.06	–0.05	0.09
25. Market volatility during ICO, value-weighted	0.10	–0.11	–0.04	–0.06	–0.06	0.14	–0.01	–0.01	–0.02	0.01	–0.01	–0.13	–0.04	0.001	–0.06
Human capital characteristics															
26. # team members	0.18	–0.04	–0.09	–0.01	–0.01	–0.46	0.08	0.07	0.04	0.07	0.06	0.40	0.18	0.12	0.13
27. # team members with technical degree	0.17	–0.003	–0.05	0.01	0.05	–0.40	0.15	0.15	0.10	0.11	0.13	0.22	0.13	0.08	0.08
28. # team members with Ph.D.	0.11	0.05	–0.005	–0.01	0.03	–0.40	0.13	0.13	0.08	0.13	0.10	0.11	0.04	0.04	0.06
29. # team members with crypto experience	0.16	–0.01	–0.03	0.07	0.05	–0.36	0.10	0.09	0.06	0.08	0.09	0.27	0.16	0.08	0.08
Social capital characteristics															
30. CF investor network centrality	0.25	0.06	0.22	0.19	0.21	0.22		0.06	0.42	–0.01	0.46	–0.05	–0.04	–0.11	–0.15
31. Startup firm network centrality	0.04	–0.03	–0.09	–0.07	–0.06	–0.40	–0.02	–0.03	–0.02	–0.02	–0.03	0.28	0.12	0.08	0.09

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

	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.
1. Funding amount, in $ (log.)																
2. 6-month BHAR, value-weighted																
3. 12-month BHAR, value-weighted																
4. 18-month BHAR, value-weighted																
5. 24-month BHAR, value-weighted																
6. CAR, value-weighted [–5,+5]																
Fund characteristics																
7. Crypto Fund																
8. Venture-style capital																
9. Hedge-style capital																
10. Specialization																
11. Diversification																
Firm characteristics																
12. Expert rating																
13. GitHub open-sourced																
14. Business model: Platform																
15. # targeted industries																
16. Ethereum blockchain																
Offering characteristics																
17. Pre-sale	–0.004															
18. Promotion scheme: Bonus	–0.001	0.06														
19. Promotion scheme: Reward	0.01	0.19	0.11													
20. KYC	–0.02	0.18	0.10	0.26												
21. # competing ICOs	0.03	0.08	0.04	0.14	0.14											
Market characteristics																
22. Bull market	0.01	–0.18	–0.09	–0.26	–0.37	–0.22										
23. Bear market	0.03	0.16	–0.01	0.18	0.22	0.63	–0.31									
24. Sideways market	–0.06	0.08	–0.08	0.07	0.15	–0.22	–0.29	–0.36								
25. Market volatility during ICO, value-weighted	0.02	–0.05	–0.01	–0.09	–0.15	0.13	0.31	0.18	–0.36							
Human capital characteristics																
26. # team members	0.04	0.12	0.06	0.15	0.24	0.07	–0.10	0.14	–0.05	–0.01						
27. # team members with technical degree	0.04	0.05	0.03	0.10	0.15	0.04	–0.04	0.12	–0.12	–0.01	0.64					
28. # team members with Ph.D.	0.05	0.001	0.05	0.01	0.11	–0.001	–0.02	0.03	–0.07	–0.03	0.35	0.41				
29. # team members with crypto experience	0.04	0.08	0.02	0.13	0.16	0.05	–0.05	0.14	–0.09	0.02	0.64	0.57	0.28			
Social capital characteristics																
30. CF investor network centrality	0.05	–0.22	0.08	–0.08	–0.18	–0.19	0.19	–0.15	–0.04	–0.05	–0.06	–0.02	–0.10	0.01		
31. Startup firm network centrality	–0.001	0.13	0.04	0.14	0.13	0.06	–0.07	0.08	0.03	0.01	0.25	0.17	0.06	0.27	–0.06	

Table A3: **Pairwise Correlations for additional CF Data**

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. CAPM-alpha, value-weighted, monthly (in %)															
2. Sharpe ratio, value-weighted, monthly	0.68														
3. Performance persistence CAPM-Alpha, value–weighted	–0.22	–0.19													
Fund characteristics															
4. Hedge-style capital	0.02	0.23	0.07												
5. Specialization	–0.08	–0.07	0.05	0.21											
6. # of investments	0.06	0.05	–0.08	–0.18	–0.73										
7. AuM, in $M	–0.02	–0.06	0.02	–0.002	–0.04	0.11									
8. # of staff	–0.10	–0.12	0.001	–0.01	0.004	–0.06	0.19								
9. Fund age, in years	0.01	–0.02	0.05	–0.12	–0.06	0.09	0.07	0.16							
10. Common law country	–0.02	0.02	–0.01	0.09	0.03	0.02	0.10	0.01	0.09						
11. Performance incentive	–0.09	0.16	0.03	0.09	0.18	–0.09	0.01	0.08	–0.02	0.01					
Fund human capital characteristics															
12. # team members with crypto experience	–0.04	–0.04	–0.03	0.13	–0.08	0.08	0.15	0.02	–0.11	–0.13	–0.12				
13. # team members with investment experience	–0.12	–0.11	–0.02	–0.04	–0.15	0.15	0.21	0.06	–0.08	–0.08	0.03	0.46			
14. # team members with Ph.D.	0.07	0.16	0.05	0.05	0.12	–0.03	–0.11	–0.05	–0.01	–0.09	0.004	0.24	0.11		
Social capital characteristic															
15. CF investor network centrality	0.25	0.29	0.03	0.49	–0.11	0.13	0.18	–0.05	–0.02	0.13	–0.002	0.16	–0.02	–0.03	