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(R)evolution in Entrepreneurial Finance? The Relationship between Cryptocurrency and Venture Capital Markets

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The Relationship between Cryptocurrency and Venture Capital Markets

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Abstract

We propose a model of staged financing where entrepreneurs choose between Initial Coin Offering (ICO) and traditional funding methods such as Venture Capital (VC). While in early stages token sales allow startups to leverage network externalities, VC's value-adding services enhance productivity in later stages. Despite the complementarity between externality effects and value-adding services, information frictions in cryptocurrency markets induce an inefficient selection equilibrium, where entrepreneurs with low-externality projects raise VC capital only to avoid adverse selection in later stages. Using data on funding rounds of blockchain startups, we provide empirical evidence for both the complementarity assumption and the selection result.

Keywords: *ICOs, Blockchain, Venture Capital, Network Effects, Cryptocurrencies, FinTech, Adverse Selection*

JEL classification: *G32, L26, D80*

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1 Introduction

In 2018, startups around the world raised \$11.6 billion in funding through Initial Coin Offerings (ICOs). Given the very recent appearance of ICOs on the financial markets scene (2013), this figure was surprisingly close to that of total capital raised by early-stage firms in the same year through "traditional" channels, such as Angel, Seed and Early Stage Venture Capital (\$12 billion).[1] The market then dropped dramatically from its peak in early 2018, leaving investors wandering whether or in what form ICO fundraising will be relevant going forward.

While economists and regulators are still scrutinizing various aspects of cryptocurrency finance, including the challenges that it can pose to monetary policy, this study focuses on its relationship with existing funding methods for startups, like Venture Capital (VC). Is there a specific, novel contribution of cryptocurrency markets to entrepreneurial finance? Can this nascent market disrupt traditional entrepreneurial finance sources and become a valid funding alternative for startups? How does regulation, or lack thereof, affect entrepreneurs' choice between VC and ICO funding? To answer these questions, we propose a theoretical framework for startup staged finance that builds on the unique comparative advantages offered by the two funding strategies. To support our theoretical results, we test our model's predictions using data on global startups funding events, firm characteristics, and output measures.

The stepping stone of our framework is the assumption that, unlike traditional VC funding, ICOs allow firms to build a sizeable initial customer base and exploit network externality effects in early stages. This is possible because digital tokens are redeemable against goods or services provided by the issuer, and therefore ICO subscribers are both investors and (potential) product users. Additionally, we conjecture that positive externality effects can be hastened by VC's active involvement in firm management through monitoring and advising services, thus further improving firm outcomes in later stages. That is, VC capital can complement token-based finance. Despite the benefits of using both funding sources sequentially, however, lack of transparency and regulatory oversight in cryptocurrency markets can limit the extent to which startups take full advantage of the complementarity between ICO and VC finance, inducing sub-optimal funding choices. In

[1] Sources: `https://assets.kpmg/content/dam/kpmg/xx/pdf/2019/01/kpmg-venture-pulse-q4-2018.pdf` and `https://icobench.com/reports/ICO_Market_Analysis_2018.pdf`, retrieved on 29th October 2019.

particular, our model results in a selection equilibrium where entrepreneurs with low-externality projects choose to forsake complementarity benefits and raise VC capital only, in order to avoid underpricing in later stages. In this sense, exclusive use of VC capital in both early and late stages is not the effect of optimal matching between project and investor types, but rather an inefficient outcome stemming from information frictions due to the opacity of the cryptocurrency markets.

We motivate the presence of such frictions by arguing that informativeness of token prices is currently modest and the efficiency of cryptocurrency marketsis far from established (see. Borri and Shakhnov [2019]). Launching an ICO and listing tokens on a cryptocurrency exchange does not involve extensive company disclosures, leaving investors with little information for making their decisions. Moreover, in the absence of proper supervision, crypto-exchanges may report inflated trading volumes to simulate higher market activity, thus attracting investors and issuers.[2] For unlisted tokens, which constitute the majority of coins in circulation, OTC trading is hindered by search frictions due to lack of intermediaries operating in this market. In short, cryptocurrency markets do not (yet) perform the role of information aggregators that finance literature traditionally ascribes to security markets.[3] In fact, concerns over lack of transparency have led several commentators to dismiss the ICO phenomenon as a fad based on regulatory loopholes and prone to frauds.

However, many specific features of ICO funding are unrelated to the regulatory framework and rest on more fundamental economic forces. Network externalities, i.e., the benefits of raising capital from many "early adopters" (users) rather than a few institutional investors, are a case in point. Several recent studies emphasize this as the prominent innovation of cryptocurrency finance (Li and Mann [2018], Cong et al. [2019], Sockin and Xiong [2018]).

We juxtapose network externality effects provided by ICO funding with the benefits of professional investment. Contrary to cryptocurrency investors who are dispersed and often remote from the issuer, institutional investors such as VCs typically provide young firms with value-adding services that range from strategic advice, monitoring, and human resources management to establishing a relationship with potential customers, suppliers, partners, and other investors (for

[2] See `https://www.wsj.com/articles/most-bitcoin-trading-faked-by-unregulated-exchanges-study-finds-11553259600?mod=hp_lead_pos7`, retrieved May 2020

[3] Grossman and Stiglitz [1980], Glosten and Milgrom [1985], Kyle [1985]

recent evidence see Gompers et al. [2019]). According to the popular outlet TechCrunch, "crypto-companies" are increasingly recognizing these benefits :

"[...] companies that raised large ICOs, including TenX and MCO, have publicly expressed interest in holding new investment rounds to bring in professional VCs. That's because money alone won't open doors, but often connections can."[4]

The quote above suggests that VC and ICO funding are not perfect substitutes, and each performs a specific role in enhancing firm success. Hence, the two funding methods are potential complements, and, if possible, firms should seek an "optimal mix" of cryptocurrency and VC capital. In practice, many startups, including those operating in technology-oriented markets and with FinTech favorable regulation, do not even attempt to diversify their funding sources away from traditional entrepreneurial finance.

To explore financing choices in this context, we propose a model of staged financing.[5] Our model features an entrepreneur who relies on outside professional (VC) and non-professional (ICO) investors to fund her business project. Investors require a share of the final output to compensate them, and entrepreneurs choose their investors by evaluating costs (dilution) and benefits of external funding. Investment takes place sequentially in two stages, and at the end of the second stage, an output is produced that depends on the entrepreneurial ability and network externalities. While project externalities are common knowledge, the entrepreneurial ability is not initially observable to either entrepreneurs or investors but is revealed to firm insiders at the end of the first stage.

During the first stage, the firm invests in advertising using available funds to subsidize the creation of a "community" of users and add new customers to the existing base. In order to finance advertisements, the entrepreneur can raise funds either from ICO or VC investors. ICO investors provide a larger initial customer "endowment", but, unlike VCs, they remain "outsiders", i.e., they do not learn the entrepreneurial ability. This is because, contrary to regulated capital markets, the lack of public information on firm performance hinders investors' ability to update their beliefs

[4] Source: https://techcrunch.com/2018/09/12/icos-are-increasingly-just-for-venture-capitalists/, retrieved on 29th October 2019

[5] The prevailing view from the existing literature on VC is that staging is a way to mitigate agency problems (Tian [2011]). The VC investor retains the option to abandon the entrepreneur's project if it fails to meet stage targets, which leads to more efficient investment decisions and better investment outcomes (e.g., Admati and Pfleiderer [1994], Gompers [1995], Kaplan and Stromberg [2003], Wang and Zhou [2004]).

on companies fundamentals before the output is finally produced. On the other hand, conditional on investing in the first stage, VCs become insiders by virtue of their direct involvement in firm management and information acquisition skills. Thus, the benefits of using VC funding in initial rounds are resolving future information asymmetries between the entrepreneur and capital markets in follow-on rounds.

After the advertisement stage, entrepreneurs can raise follow-on capital with VCs. At this stage, VCs enhance the entrepreneurial ability and boost productivity through value-adding services. Importantly, we assume that the effects of VC advising on output and firm value are proportional to the size of the customer base, i.e., we assume complementarity between the two funding methods.

What funding method(s) do entrepreneurs choose in equilibrium? The complementarity assumption implies that, in the absence of frictions, the output maximizing funding sequence features ICO in first rounds and VC in follow-on rounds. Due to asymmetric information, however, second stage VC funding can be too expensive for high ability entrepreneurs who started their funding sequence with an ICO. This is because, similar to Myers and Majluf [1984], outside investors cannot separate high versus low ability entrepreneurs and price rounds accordingly. As a consequence, high ability entrepreneurs do not seek follow-on (VC) capital. In anticipation of this potential outcome, the first stage decision to launch an ICO hinges on the trade-off between access to a large customer base and costs of adverse selection (underpricing) in follow-on rounds. Crucially, this choice ultimately depends on the importance of network effects, which amplify the size of the initial customer base, thus increasing output. Entrepreneurs with low network externalities seek VC funding first, as they enjoy only small benefits from a sizeable initial customer base, while entrepreneurs with high network externalities select into crypto-finance. Importantly, this selection equilibrium is not the consequence of optimal startup-investor matching, where VC investment is better suited for firms with low network externality effects. Instead, it is the result of the constraints imposed by information frictions. In the absence of these frictions, optimal funding always involves both ICO and VC. The order of the optimal funding sequence - ICO first and VC later - arises from the simplifying assumption that ICOs can only be held in the initial stages, which we impose in accordance with empirical evidence showing that ICO are usually firm's first financing event, but is not essential for the qualitative results.[6]

To investigate the empirical relevance of our theoretical framework, we collect data on blockchain-based startups founded after 2014 and on their financing events. Differently from previous studies that use information freely provided by data analytics websites specialized on cryptocurrencies (e.g., ICObench.com), we retrieve data on ICO (and VC) financing events from Crunchbase, an established commercial online platform that provides information on funding rounds, business details and news of private and public companies. While our ICO sample contains fewer observations than other datasets, it has two main advantages. The first is that it allows us to track all company funding rounds, including non-ICO ones. The second is that it most likely excludes "scams" and fraudulent initiatives. Therefore, given the increasing regulatory actions in the decentralized finance space, our sample may resemble more closely the ICO market going forward.[7]

Our dataset consists of 1,218 firms and 2,281 funding rounds. Approximately one in four rounds is an ICO, while the rest are VC rounds, mostly Seed and Early Stage. ICOs and traditional VC funding are not mutually exclusive, as 44% of firms that raise funds with an ICO also receive VC funding, suggesting that some startups exploit the benefits of tapping different capital markets. We collect information on firms' outcomes in terms of employment and web traffic. Using textual analysis, we build an index that measures potential network externalities based on business descriptions. We document three main findings. First, the probability of issuing tokens is strongly correlated with the presence of potential network externalities, as measured by our index. This is consistent with the self-selection equilibrium result. Second, outputs of ICO funded projects are increasing with network externality effects while outputs of non-ICO (or VC-only) funded projects are independent of network externality. Seen through the lenses of our model, this is because entrepreneurs running projects with externality effects below the selection threshold choose VC funding in early rounds and forsake externality gains altogether in order to avoid adverse selection in follow-on rounds. Third, the effects of externality on outputs are larger for projects with mixed

[6] The fact that firms may seek VC as their first round and then move to issuing cryptocurrency in later stages is confirmed by the increasingly common presence in VCs term sheets of clauses that grant investors rights on future token issues.

[7] In April 2019, the SEC articulated a framework for "Investment Contract" analysis of digital assets that provides guidelines to assess whether the U.S. federal securities laws apply to ICOs (https://www.sec.gov/corpfin/framework-investment-contract-analysis-digital-assets). China's Office for Special Remediation of Internet Financial Risks introduced a blanket ban on ICOs in September 2017.

funding sources (both ICO and VC) than projects funded only with ICO. This result suggests that building a community of early adopters through an ICO can be further amplified by VCs' value-adding services. In other words, VC and cryptocurrency markets are complements, as conjectured in our model. Taken all together, our evidence suggests that resolving information asymmetries in cryptocurrency markets, for example, via mandatory disclosure requirements, can improve the efficiency of entrepreneurial finance markets by allowing firms to exploit the complementarity between network effects and professional investors advise.

This study contributes to existing finance literature in three ways. First, we add to previous characterizations of the cryptocurrency market (Howell et al. [2018], Hu et al. [2018]) by investigating its links with established private capital markets. Second, we build on existing theories on the rationales of token-based funding (Cong et al. [2019], Sockin and Xiong [2018], Biais et al. [2018]), and in particular on network externalities based theories, and offer some early empirical evidence. Moreover, as in Lee and Parlour [2018], Bakos and Halaburda [2019], Catalini and Gans [2018], and Chod and Lyandres [2018], we explicitly consider the trade-off between "old" (VC) and "new" (ICO) funding methods. Differently from these studies, however, we micro-found the VC side of this trade-off with previous empirical evidence on VCs' value-adding services documented by entrepreneurial finance research (Gompers et al. [2019], Amornsiripanitch et al. [2017], Sørensen [2007], Hellmann and Puri [2002], Lerner [1995]). Finally, this study contributes to the growing literature on the effects of financial development achieved through technological innovations (Frost et al. [2019], Thakor [2019], De Roure et al. [2019], Buchak et al. [2018], Claessens et al. [2018], Philippon [2016]). Token-based finance contributes to financial development not merely through broader and easier access to external funding but also, and more importantly, by facilitating the creation of large networks of users. In the context of FinTech, this feature is unique to ICO funding.

The rest of this paper is organized as follows. In Section 2, we give a brief overview of the ICO process. In Section 3, we present our model, and in Section 4, we list the model's testable predictions. We illustrate data and relevant descriptive statistics in Section 5, and we present our empirical findings in Section 6. Section 7 concludes.

2 An ICO primer

An Initial Coin Offering (ICO) is a financing event in which a company sells coins ("tokens") in exchange for fiat money or cryptocurrencies (typically Bitcoin or Ethereum) in order to fund its operations. Tokens are unregistered digital claims against future provision of the issuer's products or services, "utility" tokens, or against part of the issuer's future cash flows, "security" token.[8] Utility tokens do not grant any voting, board, redemption, liquidation, or residual cash flow right. Most coins are presented by issuers in their marketing material as utility tokens, although this definition has been challenged by some regulators seeking to discipline the use of ICOs as a way to circumvent Securities Laws (see Howell et al. [2018] for further discussion on the current regulatory framework).

Differently from VC deals which are typically negotiated behind closed doors, ICOs are advertised with the general public. Issuers disseminate an online document, the "white paper", that can vary in length (from a single page to close to one hundred) and content. White papers generally contain information on the project, the founding team, and details of the offering. Investors can participate in the offering and purchase tokens on the company's website during a pre-specified period of time, typically between 1 and 6 months.

Once the offering is completed, the issuer chooses whether to list its token on an exchange, i.e. a privately owned online platform where users meet to buy and sell cryptocurrencies. Currently there exist over 500 exchanges, which differ in trading volumes, range of currencies traded, and users/issuers fees. Listing may not be necessary if tokens are intended to be traded OTC.

Cryptocurrency markets do not rely on central clearing authorities or financial intermediaries to validate trades and establish ownership. Instead, book-keeping and settlement of transactions are fully automatized by blockchain technologies, i.e. distributed public transaction ledgers maintained by a network of computers. Other relevant applications of blockchain technologies are smart contracts, i.e. computer protocols that execute and enforce contracts without human intervention. In the context of token-based funding, smart contracts can be employed in numerous ways, for example in order to automatically reimburse initial investors if certain funding goals are not reached

[8]For a theory of security and utility token funding mix optimality see Mayer [2019]

within a set period of time, to facilitate voting of token-holders on company issues, to enforce voting outcomes, or to implement token vesting schemes.[9] Most startups that use blockchain based finance and cryptocurrencies also employ blockchain technologies for business purposes.

3 Model

3.1 Overview

We provide a model of two-stage financing where entrepreneurs can raise funds either from ICO or VC investors in exchange for a share of the project's output. During the first stage, which starts at $t = 0$, entrepreneurs use funds to advertise their new product or service and build their customer base. For example, they can promote a "beta" version of their service or offer free samples of their product. Actual commercialization starts at $t = 1$ and generates output, V, at the end of the second stage ($t = 2$). V depends on the final number of customers reached in the first stage, N, and on profitability, z, so that $V = zN$. Profitability z is initially unknown to either entrepreneurs and investors. It depends on the quality of the product, e.g. its uniqueness, ease of use, design etc., in other words, it depends on entrepreneurial ability ω^i, which is revealed to the firm's insiders at $t = 1$, i.e. at the end of the first stage. Ability is exogenously given and it can be either high, ω^H, with probability p, or low, ω^L, with probability $1 - p$, so that expected ability at $t = 0$ is $\bar{\omega} = p\omega^H + (1 - p)\,\omega^L$. Profitability also depends on the effectiveness of commercialization efforts in the second stage. Thus, it depends on funding choices at $t = 1$. This is because at this stage, VC (but not ICO) investors can offer value-adding advising services, helping the startup enhance its cash flows, so that $z = \omega^i + h$. Since raising capital on cryptocurrency markets in the second stage adds no value to entrepreneurs, the ICO funding option is always weakly dominated by VC or no funding at all in second stages. This is consistent with the empirical observation that ICOs typically correspond to firm's very first funding event.

At $t = 0$, in the first funding round, the entrepreneur sells claims either to a VC (in the form of equity shares) or to ICO investors (in the form of tokens) in exchange for K units of capital, where

[9] For a theory on the relationship between token-based finance and smart contracts see Tsoukalas and Hemenway Falk [2018]

the amount K is entrepreneur's choice. If the initial investment comes from a VC, investors buy a share of the project's future profits, q_1^{VC}. By opting for an ICO instead, the entrepreneur organizes a token sale and keeps a fraction of tokens $1 - q_1^{ICO}$ to herself. The entrepreneur also commits to only accept tokens as medium-of-exchange on the platform, which is in the spirit of Schilling and Uhlig [2019]. Therefore we can think of tokens as claims against a share of total future output V.

At the end of the first stage ω^i is revealed to firm's insiders. We include in the definition of insiders both the entrepreneurs and VC investors, if they provided first stage funding. This is because typically VCs are directly involved in the management of the companies they invest in, allowing them to acquire private knowledge on firm's growth opportunities. Differently from VCs, cryptocurrency investors are dispersed and do not take any active role in managing or monitoring the firm. Therefore they remain "outsiders", that is unaware of firm's actual profitability, even after investing.[10] In other words, ICO investors lack VC's ability to acquire and process relevant information on entrepreneurial skills. Since this information is valuable for investors in follow-on rounds, an entrepreneur who opts for ICO instead of VC funding in the first stage is exposed to asymmetric information and adverse selection when seeking additional capital in the second stage.

In the second funding round, the entrepreneur decides whether to raise additional capital κ from VC investors to boost profitability by h. We assume that κ and h are fixed parameters, constant across firms. If the entrepreneur opts for additional funding, she sells an additional share (q_2^{VC}) of the output that remained in her possession after the first period, $(\left(1 - q_1^I\right) V)$.

In the last period, the output is produced and split between investors and entrepreneurs according to agreed shares.

To summarize, the model unfolds according to the following time line

- $t = 0$: First Round. Entrepreneurs choose ICO vs VC and investment amount K. Funds are employed to build customer base N.
- $t = 1$: Second Round. Firm insiders (Entrepreneurs and insider VC) observe ω^i. Entrepreneurs decide whether to raise additional capital, κ, from VC, or stop investing.

[10] This also implies that token price at $t = 1$ is uninformative with respect of true ω

- $t = 2$: Cash Flows occur. Firm value is $V = zN$. Profitability z equals $\omega^i + h$, if additional VC capital was raised in the previous period, or ω^i otherwise.

Finally, we assume that entrepreneurs, ICO investors and VCs are risk neutral. Intuitively, different degrees of risk aversion among ICO and VC investors make funding in one market more expensive as compared to the other. We sketch a solution for our model when ICO investors are risk averse in Appendix A. Both investor types have deep pockets and capital markets are competitive. For simplicity, we set the investor outside option equal to zero.

Initial Customer Base and the Role of Externalities

In a market with network effects (e.g. online games, dating websites, or financial exchanges), a customer's willingness to pay for a certain product or service increases with the number of current users, i.e. with network's size (Katz and Shapiro [1986]). By building a large initial base of customers-investors, successful ICOs can generate a "gravitational" mass that attracts new adopters, further enlarging the network and fostering firm success.[11] This feature is particularly valuable in "marketplace" economies, i.e. industries based on intermediation via online platforms, where new concepts can be easily imitated by competitors and first-mover advantage can quickly dissolve. Since traditional entrepreneurial funding is generally provided by few institutional investors (banks, VC funds) who do not purchase the product or service of the funded firm and therefore can not directly contribute to hastening network effects, ICO funding offers benefits that are novel and distinct from more established methods.[12]

We incorporate network externality effects in the following way. The funds obtained in the first stage are spent to expand the initial customers "endowment" C_I. We assume that C_I depends on the funding method, in particular $C_{VC} = 1$ and $C_{ICO} = \mu > 1$. We use this simple assumption to capture the idea that ICO funding gives access to a larger base of investors who are also potential users/customers. Of course, not all token investors are prospective clients and the value of μ

[11] Of course, network externalities considerations are less relevant for issuers of "security" rather than "utility" tokens.

[12] Other benefits of ICO funding are demand discovery, as in Catalini and Gans [2018], and retention of control, as in Chod and Lyandres [2018], as ICOs allow founders to fund themselves without equity commitment or with very limited, if any, loss of control on business operations

varies with the nature of the business. Projects that cater to business clients (business-to-business, or B2B) have lower μ than projects that cater to retail clients (business-to-consumer, or B2C). Crucially, the initial customers endowement is additionally magnified by project-specific network externalities $\varepsilon \geq 0$. In other words, the willingness of new customers to use the service and join the "community" increases with the number of existing customers. We model final number of customers accordingly as $N = (C_I)^{\varepsilon} K^{\alpha}$, where $\alpha \in (0, \bar{\alpha})$ with $\bar{\alpha} < 1$ captures decreasing returns of the advertising technology employed in the first stage and K is the amount of capital invested.

Notice that since VC funding affects z (through h) and ICO affects N (through $C_{ICO} = \mu$), we implicitely assume complementarity between the two funding methods, as final firm value is $V = zN$. Moreover, by expanding the customer base, externalities amplify the effects on outcomes of the interaction between ICO and VC funding. For example, everything else equal, the difference in output between a project financed with both ICO and VC and a project funded only with VC is equal to $h\left(\mu^{\varepsilon} - 1\right) K^{\alpha}$, which is increasing in ε. Similarly, the difference in output between a project financed with both ICO and VC and a project funded only with ICO is equal to $h\mu^{\varepsilon} K^{\alpha}$. In other words, externalities intensify the complementarity between cryptocurrency and VC funding.

Adverse Selection and VC Efficiency

Cryptocurrency markets are arguably opaque. Companies that fund themselves with digital claims have no reporting requirements. Importantly, investors can not gather additional information on firms beyond what the management decides to disclose. This is in sharp contrast with the active information acquisition/production process that typically characterizes VC staged investments (Bergemann and Hege [1998]), where several investment contract features are contingent on new information flows (Kaplan and Stromberg [2003]). Moreover, since ICO funding is relatively accessible, the quality of firms that issue cryptocurrency is greatly heterogeneous, with startups ranging between promising high-growth projects to likely failures. Thus, companies that used token-based funding may face adverse selection when raising capital from alternative sources in subsequent financing stages. The following assumptions emphasize these features.

Assumption 1. The productivity gains from VC investing in the second stage are small enough to guarantee a unique separating equilibrium where only low ability entrepreneurs raise capital from uninformed (outsider) VC investors.

Assumption 2. The productivity gains from VC investing are large enough that, in the absence of externality effects, ICO funding in first rounds is never optimal.

Intuitively, the two assumptions above combined result in an upper and lower bound for the marginal return on second round VC investment $\frac{h}{\kappa}$. Therefore, holding h constant, these assumptions can be expressed as constraints on parameter κ, i.e. $\kappa \in [\underline{\kappa}, \bar{\kappa}]$. We provide the analytical expressions for $\underline{\kappa}$ and $\bar{\kappa}$ in Section 4.1.1 and Section 4.1.3 respectively.

We solve the model by backward induction, starting from optimal investment choices in the second stage, conditional on funding decisions in the first stage. In the first stage the entrepreneur decides which funding method to use and the optimal investment level. The intuition for the analytical solution (provided in the next section) is as follows. ICO funding provides entrepreneurs with a larger customers base in first rounds, while VCs boosts profitability in second round. With symmetric information, these two funding methods are natural complements and the best funding sequence is always ICO-VC. However, asymmetric information and large dispersion in entrepreneurial ability (both reasonable assumptions in the context of early stage finance) imply that second round funding may involve underpricing (and underinvestment) for highly productive firms. The potential loss in terms of extra-profitability due to adverse selection in second rounds outweigh network benefits for firms with low externalities. These firms are willing to trade larger initial customer bases for VC value-adding services and therefore choose to start their funding sequence with VC. Here VC and ICO become imperfect substitutes.

3.1.1 First Round: ICO

Second Stage

At $t = 1$, the expected payoff for a VC investing κ for a share q_2^{VC} of final output is

$$Y_1^{VC} = q_2^{VC} \left(1 - q_1^{ICO}\right) E_1^V (V) - \kappa$$

where $E_1^V(V)$ denotes VC's expectation at $t = 1$ on final project cash flows and q_1^{ICO} is the share of output sold to ICO investors in the first round. Since VCs did not invest in first round, they are outsiders and therefore unaware of the actual ability of the entrepreneur. This setup can generate both a pooling and a separating equilibrium. We start by analyzing the pooling equilibrium, i.e. the equilibrium where entrepreneurs with both high and low ability raise VC funding.

If VCs anticipate both high and low ability entrepreneurs seek funding then the expected final firm value is equal to average profitability, $\bar{z} = p\omega^H + (1-p)\,\omega^L + h$, times final customer base, that is $E_1^V(V) = (\bar{\omega} + h)(\mu)^{\varepsilon} K^{\alpha} = \bar{z}N$. By setting Y_2^{VC} equal to VC's outside option (zero), we find the VC share

$$q_2^{VC} = \frac{\kappa}{\left(1 - q_1^{ICO}\right)\bar{z}N}$$

Contrary to VCs, by the end of the first stage entrepreneurs know their profitability type , i.e. they know whether $\omega^i = \omega^H$ or $\omega^i = \omega^L$. When considering whether to raise additional capital with a VC or no capital at all the entrepreneur compares the payoff from the first option

$$X_1^E(ICO, VC) = \left(1 - q_2^{VC}\right)\left(1 - q_1^{ICO}\right)\left(\omega^i + h\right)N$$

with the payoff from the second option

$$X_1^E(ICO) = \left(1 - q_1^{ICO}\right)\left(\omega^i\right)N$$

It follows that the entrepreneur chooses not to raise any more capital if $\omega^i \geq h\left(\frac{1}{q_2^{VC}} - 1\right)$.

This implies that for $\omega^H \geq h\left(\frac{\left(1-q_1^{ICO}\right)\bar{z}N}{\kappa} - 1\right)$ there is no pooling equilibrium where both low and high types raise second stage funding. Instead, a separating equilibrium exists where only low ability entrepreneurs raise second rounds with VCs and high ability entrepreneurs refrain from raising additional capital. The intuition is that, similar to Myers and Majluf [1984], with asymmetric information the benefits of VC's support in terms of enhanced productivity can be too low when compared to the loss due to ownership dilution. This is especially true for entrepreneurs with high ability, who choose to forgo follow-on investments.

Assumption 1 states that the condition for a unique separating equilibrium holds. In particular, we can write this condition as follows

$$\frac{h}{\kappa} \leq \frac{\omega^H + h}{(\bar{\omega} + h) N} \tag{1}$$

Equation 1 effectively imposes a maximum value on the marginal return of second stage VC investment. Notice that this constraint depends on $N$and hence on the endogenous choice of optimal K (K^*). We restate this condition in the next subsection, after we solve for K^*.

In the separating equilibrium, only low ability entrepreneurs seek second round VC funding. VC's share is as follows

$$q_2^{VC} = \frac{\kappa}{\left(1 - q_1^{ICO}\right)\left(\omega^L + h\right) N}$$

First Stage

At $t = 0$, the payoff for ICO investors contributing K is

$$Y_0^{ICO} = q_1^{ICO} E_0^{ICO}(V) - K$$

where $E_0^{ICO}(V)$ is the expected utility of firm value V. We derive the equilibrium share by setting Y_0^{ICO} equal to invetsors' outside option, zero. Thus

$$q_1^{ICO} = \frac{K}{E_0^{ICO}(V)}$$

Just like entrepreneurs, ICO investors anticipate that VC will only contribute capital in the second round if $\omega^i = \omega^L$ and therefore profitability will receive a boost in the second stage only with probability $1 - p$. We define $E_0^{ICO}(V) = \check{z} N$ where $\check{z} = p\omega^H + (1 - p)\left(\omega^L + h\right)$.

Given optimal strategies in stages one and two, entrepreneurs' expected utility is

$$p\left(1 - q_1^{ICO}\right)\omega^H N + (1 - p)\left(1 - q_1^{ICO}\right)\left(1 - q_2^{VC}\right)\left(\omega^L + h\right) N =$$

$$= \check{z}N - K - (1-p)\,\kappa \tag{2}$$

with $N = (\mu)^{\varepsilon} K^{\alpha}$. Entrepreneurs receive the expected value of the project $(\check{z}N)$ net of investors' expected compensation. Due to asymmetric information, the second funding stage occurs only with probability $1-p$.

Finally, entrepreneurs maximize expected utility (2) by setting initial investment K as

$$K^{*}_{ICO} = \mu^{\frac{\varepsilon}{1-\alpha}} (\alpha \check{z})^{\frac{1}{1-\alpha}}$$

We can then rewrite Assumption 1 as expressed in (1) by replacing N with $\mu^{\varepsilon} K^{*}_{ICO}$ .We have

$$\kappa \geq \left[\frac{\bar{z}}{\bar{z} + (1-p)\left(\omega^{H} - \omega^{L}\right)}\right] \frac{\left[\mu^{\varepsilon} (\alpha \check{z})^{\alpha}\right]^{\frac{1}{\alpha-1}}}{h} \equiv \underline{\kappa} > 0$$

3.1.2 First Round: VC

We now analyze the second round equilibrium when first rounds are funded with VC. Having financed the first stage, the VC learns entrepreneurial ability before the second round, i.e. no asymmetric information exists in the second stage environment. Therefore we have that VC's equilibrium output shares are

$$q^{VC}_{2,H} = \frac{\kappa}{\left(1 - q^{VC}_{1}\right)\left(\omega^{H} + h\right) N}$$

$$q^{VC}_{2,L} = \frac{\kappa}{\left(1 - q^{VC}_{1}\right)\left(\omega^{L} + h\right) N}$$

Since second stage funding is available to both low and high types, the share of ownership required by VC at $t=0$, when entrepreneurial ability is unknown is

$$q^{VC}_{1} = \frac{K}{(\bar{\omega} + h)\, N}$$

with $\bar{\omega} = p\omega^{H} + (1-p)\,\omega^{L}$. Given required output shares in stage one and two, entrepreneurs' expected utility is

$$\left(1-q_1^{VC}\right)\left(1-E\left(q_{2,i}^{VC}\right)\right)(\bar{\omega}+h)\,N=$$

$$=\bar{z}N-K-\kappa \tag{3}$$

with $N=K^{\alpha}$ and $\bar{z}=\bar{\omega}+h=\check{z}+ph$. Not surprisingly, entrepreneurs receive the whole expected net present value of the project.

Finally, entrepreneurs maximize expected utility (2) by setting initial investment K as

$$K_{VC}^{*}=(\alpha\bar{z})^{\frac{1}{1-\alpha}}$$

3.1.3 VC or ICO?

At time $t=0$ the entrepreneur faces the choice of whether to raise capital with a VC or through an ICO. On the one hand, ICOs allow entrepreneurs to build a larger initial community of customers. This is particularly valuable for projects that cater to retail consumers rather than other businesses, i.e. projects with high values of μ. On the other hand, raising funds with ICO investors in the first stage does not solve asymmetric information problems and therefore, in the second round, entrepreneurs of high ability miss on the opportunity of increasing profitability with VCs' guidance. However, since investing in the second stage has net present value equal to $hN-\kappa$, larger investment requirements, or, in other words, lower VC efficiency, decrease the value of this opportunity.

Finally, let us focus on parameter ε. Network externalities increase final output by expanding the initial customer base. Therefore, large externality effects (combined with the network provided by ICO investors) can potentially compensate for lost value-adding services provided by VCs in second rounds. Thus, entrepreneurs in charge of projects of this type may opt for ICO funding in first rounds, despite this choice involves adverse selection issues in second rounds. Projects with low network externalities instead are financed with VCs, as entrepreneurs are willing to trade smaller networks for profit enhancing services.

To see these results, consider an entrepreneur choosing whether to raise her first round via

ICO or with a VC. She compares utilities in equation 2) and 3). ICO is preferred if the following condition holds

$$f(\varepsilon) = \Phi(\alpha)(\bar{z})^{\frac{1}{1-\alpha}} \left[\mu^{\frac{\varepsilon}{1-\alpha}} \left(\frac{\check{z}}{\bar{z}} \right)^{\frac{1}{1-\alpha}} - 1 \right] + p\kappa \geq 0 \tag{4}$$

where $\Phi(\alpha) = \alpha^{\frac{1}{1-\alpha}} \left(\alpha^{-1} - 1 \right)$

Recall that Assumption 2 states that in the absence of externality effects ($\varepsilon = 0$), ICO funding in first rounds is never optimal. This is equivalent to setting

$$\kappa \leq \left[\frac{\bar{z}^{\frac{1}{1-\alpha}} - (\check{z})^{\frac{1}{1-\alpha}}}{p} \right] \Phi(\alpha) \equiv \bar{\kappa}$$

with $\bar{\kappa} > \underline{\kappa}$ (see Appendix B). Condition 4 combined with Assumption 2 above implies that ICO is preferred when network externalities are relatively large. More specifically, there exists a threshold level ε^* such that for $\epsilon \geq \varepsilon^*$ ICO funding is the optimal strategy, while VC is selected when $\epsilon < \varepsilon^*$. The existence and uniqueness of ε^* is guaranteed by the fact that $f(0) < 0$ (by Assumption 2) and $f(\varepsilon)$ is continuous in $\mathbb{R}$ and monotonically increasing in ε.

To conclude, our model predicts that startups self select into ICO or VC funding in early stages depending on the network externality effects that characterize their projects. In particular, ICO (VC) funding is chosen when externality effects are relatively large (small). This happens despite the presence of complementarities between the two funding methods, which, in the absence of frictions, would induce entrepreneurs to optimally start their funding campaign with cryptocurrencies and then move to VC investment in subsequent stages, in order to exploit the benefits of both markets. This sub-optimal sorting equilibrium is due to asymmetric information in later funding stages. Specifically, differently from VC funding, where staging alleviates asymmetric information by revealing firm's quality to investors thus facilitating follow-on funding, cryptocurrency markets do not "produce" additional information.

4 Testable Predictions

Despite the many simplifying assumptions that we employ in order to preserve tractability, the model offers the following novel insight. Firms select funding method based on network externality effect, with low-externality projects being funded with VC capital. However, this is not because VC funding offers specific advantages to low externality projects but rather because informational frictions make it more convenient for these firms to share private information with VC (and obtain fairly priced second round funding) rather than building a large customer base right away with an ICO. Selection does not arise as the optimal financing policy but as the result of the trade-off between the benefits of complementarity and the costs of underinvestment.

The following model predictions stem from both the selection result and the complementarity assumption. They can be empirically tested conditionally on the availability of observable measures of output, externality, and funding methods. We do so in Section ?, after presenting data and methodology in Section ?

1. Projects characterized by high network externality effects are more likely financed with ICOs, i.e. $E(\varepsilon \mid ICO) > E(\varepsilon \mid VC)$. This is a direct implication of the selection equilibrium.

2. Outputs of ICO funded projects are increasing in network externality effects since $V_{ICO} = (\check{z})\,\mu^{\frac{\varepsilon}{1-\alpha}}(\alpha\check{z})^{\frac{\alpha}{1-\alpha}}$. Outputs of non-ICO (or VC-only) funded projects are independent of network externality effects since $V_{VC} = (\bar{z})(\alpha\bar{z})^{\frac{\alpha}{1-\alpha}}$. This is because entrepreneurs running projects with externality effect below the threshold ε^* forsake externality gains altogether in order to avoid adverse selection in follow-on rounds. Moreover, startups that receive first funding rounds via an ICO only receive follow-on capital with probability $p < 1$.

3. The effects of externality on outputs may be larger for projects with mixed funding source (both ICO and VC) than project funded only with ICO. To see this result consider the outcomes of the ICO-VC and ICO-only projects

$$V_{ICO-only} = \omega^H \mu^\varepsilon K^*_{ICO}$$

$$V_{ICO-VC} = \left(\omega^L + h\right) \mu^{\varepsilon} K^*_{ICO}$$

Since $\omega^H > \omega^L$, the condition $\frac{\partial V_{ICO-only}}{\partial \varepsilon} > \frac{\partial V_{ICO-VC}}{\partial \varepsilon}$ can only hold in presence of an interaction between VC contribution to profitability (h) and the customer base N, which, with ICO funding, is increasing in externality effects. Said differently, larger externality effects for the funding sequence ICO-VC as compared to ICO-only are due to the complementarity of the two funding sources.

5 Data

Our main data source is Crunchbase, a commercial online platform that provides information about companies' funding rounds (conducted both in private and public capital markets), founding members and news. Originally built in 2007 to track technology startups featured in the outlet TechCrunch, Crunchbase now contains data on new and established firms operating in different sectors across the world.[13] We collect information on startups founded after 2014 and on their financing events. We focus on startups that include the word "blockchain" in their business description. The reason for this choice is that entrepreneurs managing these firms must be familiar with the blockchain technology, which is closely related to cryptocurrencies, so that it is reasonable to assume that they include ICOs as possible financing options to consider. Our dataset consists of 1,218 firms and 2,281 funding rounds.

Differently from most previous studies in entrepreneurial finance, issuers are not predominantly located in North America, as Asia and Europe each represent approximately 30% and 27% of the sample respectively (Table 1). Table 2 illustrates additional firm characteristics. The typical founding team comprises of 2 members and women represent 7% of the team on average. We also collect information on founders' visibility on media outlets (i.e. number of articles referring to the founder), experience (i.e. number of companies founded, including the current one), exits and education (i.e. whether she attended a top school).[14] We aggregate this information at the

[13] Crunchbase sources its data through investors' voluntary submissions, AI and machine learning, users' contributions and an in-house data team who provides manual data validation and curation. See https://www.crunchbase.com

[14] We define top schools as the 100 education institutions that count the largest number of entrepreneurs among their alumni

founders-team level.[15]

Interestingly, ICOs and traditional VC funding are not mutually exclusive. In fact, approximately 44% of firms that raised funds with an ICO also received VC funding.

Since all the firms in the sample are extremely young and we have no public financial statements available, we measure real outcomes in terms of employment and web traffic (average number of monthly visits) both measured as of June 2019. 43% of firms in our sample have a headcount larger than 10 and the average web traffic is almost 60 thousand visits per month. Web traffic figures however are quite dispersed. Figure 1 further shows the distribution of web traffic for ICO (whether alone or along with VC) and VC-only funded firms.

Among all the funding rounds, 24% are Initial Coin Offerings. Other funding types are mostly seed and early stage rounds (Figure 2). We refer to all rounds other than ICOs as VC rounds for brevity. Table 3 shows descriptive statistics on rounds by funding type (ICO and VC). ICOs are considerably larger than other rounds. Consistently with our model, ICOs are less likely to have a follow-on round. Conditional on receiving an additional round of funding, most of the times VC rounds are followed by larger capital injections, i.e. the median StepUp is larger. ICO and VC rounds do not differ substantially in terms of number of investors. While this last point may seem in contradiction with the idea of a dispersed investors' base for ICOs, it is necessary to recall that our data are retrieved from voluntary disclosures, and it is unlikely that all participants in an ICO are interested in letting the general public know about their investments. Reported investors in ICOs are most likely institutional investors such as specialized hedge funds.

5.1 Measuring Potential Network Effects

In describing the concept of positive network externalities, Katz and Shapiro [1985] use the following example: "The utility that a consumer derives from purchasing a telephone [...] clearly depends on the number of other households or businesses that have joined the telephone network" (p.424). It is easy to extend this example to include networks based on new technologies, such as online dating,

[15] We could not match all founders with the corresponding people dataset in Crunchbase. When none of the founders is found in the Crunchbase dataset the team level data is treated as missing. When we match all or some of the founders, missing information at the individual level is treated as zero. For example, if we can match all founders of a company but none of them has information on past experience we set the aggregate experience value at zero.

gaming, or marketplace networks, where the willingness of a new costumer to join the network increases with the size of the current costumer base. Token based funding offers the possibility of creating a large initial costumer base, thus exploiting network externalities to boost growth. Several studies emphasize the property of hastening network effects in early stages as a relevant rationale for ICOs. For example Bakos and Halaburda [2019] show that in presence of capital constraints, token-based funding reduces the need to subsidize early adopters, lowering the costs associated with coordination problems.

We measure potential network externality for firms in our sample using simple textual analysis. Each firm in Crunchbase is associated with one or more categories, that is one or two words that describe the line of business in which the company operates. Examples of categories include: Banking, Cyber Security, e-Commerce. Among the most represented categories in our sample, we identify those that signal potentially large network effects and we label them as Network Keywords. Network Keywords are: Gaming, Communities, Platform, Messaging, Open Source, Auction, Portals, Exchange, Developer, Collaboration, Delivery, Peer, Network, Marketplace. We then construct our indexe of potential network externalities, *Externality*, by counting the number of times Network Keywords are mentioned in each company's short business description.[16] In our sample, 38% of firms exhibit positive potential network externalities. The index *Externality* ranges from 0 to 3 (with a mean of 0.44).

5.2 Selection Issues in ICO Data

Our records on ICO funding rounds are significantly fewer than the numbers reported in different data sources. For example, a widely used website for ICO tracking, ICObench.com (`https://icobench.com/`), shows records of over 3,000 ICOs in the period 2015-2018.[17] To investigate potential selection issues we match ICOs in our dataset with records in ICObench, using website urls as identifiers.

Part of the information provided on ICObench.com is retrieved from white papers. In white papers, issuers may disclose information on whether a preICO sale, i.e. a token sale restricted to

[16] Descriptions comprise of 12 words on average

[17] See Lee et al. [2019] and Borri and Shakhnov [2019]

only few investors at discounted prices, was or is to be conducted, and whether a bonus scheme is in place where early investors receive a discount on the token price. PreICO sales and bonus structures are typically used by issuers to attract investors. White papers also contain information on the total proportion of tokens distributed with the public and on vested tokens, as it is fairly common for entrepreneurs to retain a portion of the tokens issued. Additionally issuers indicate whether the offering is conditional to a softcap, i.e. minimum amount of funds raised below which the offering is withdrawn, and/or a hardcap, i.e. a maximum amount of funds that, if raised, terminates the offering. Retention of vested tokens and the use of soft/hardcaps are both devices used by issuers to commit to efficient allocation of resources, in order to prevent market failures due to moral hazard.

Combining white papers with other sources, ICObench provides data on the issuer, such as location, team members, media presence, i.e. channels through which the company advertises its project (e.g. Twitter, GitHub, Facebook etc.), and details of the offering, including amount raised, proportion of tokens distributed to the public (rather than retained by the firm managers), ICO start and end dates, pre-ICO (if any) start and end dates, bonus schedule (if any), currencies accepted in exchange for tokens, hardcap and softcap (if any), the exchange(s) on which the tokens will be traded, company's plan for future development and funding ("roadmap"), and whether any of the team members passed a KYC verification procedure.[18] Moreover, ICObench provides a rating for each offering, which is a combination of an algorithm-based assessment and ratings provided by independent contributing experts. The rating algorithm evaluates team's expertise, availability of information and transparency, media presence and marketing material. Experts' ratings are weighted by contributors' expertise, years of experience in the field, and possible available publications.

We compare our sample with the ICObench "universe" along various dimensions (Tables 4 to 6). ICOs in our sample appear to be considerably larger than those in the comparison sample (approximately three times). This is not entirely surprising as Crunchbase is likely to collect information on the largest deals, as those are more likely to be reported on specialized media such

[18] Know Your Costumer (KYC) is the process of verifying the identity and suitability of potential clients, business partners or investors. It includes the collection and analysis of basic personal information.

as blogs or news outlets. Whether this is related to firm quality is less clear. While companies in our sample have larger teams, more media presence and better ratings, average differences along these dimensions, all statistically significant, are fairly small. In the case of ratings, for example, the average difference is only 10% and there is no difference in median values. Additionally, while retaining a larger proportion of tokens issued (49% vs 44%) may signal stronger commitment on the side of founders (Davydiuk et al. [2019]), the less frequent use of hardcap and softcap provisions in our sample may indicate weaker discipline in the management of resources and inflation control. In both samples 11% of companies accept fiat currency, along with cryptocurrencies such as Bitcoin or Ethereum, in exchange for tokens. Accepting fiat money suggests legitimacy of the business as exchanges in fiat can be easily tracked by regulatory and judiciary authorities. On the other hand, companies in our sample seem to offer less transparency as they are less likely to provide investors with a roadmap (81% vs 89%) and KYC verification (47% vs 58%). Finally, companies in our sample are also less likely to offer incentives to early investors through bonus schemes (37% vs 45%) and preICO sales (40% vs 50%).[19]

Since potential network externalities are crucial for our analysis, we compute an externality measure for the two samples using the same procedure described above applied to the company description provided by ICObench. Importantly, our sample does not differ from the "universe" in terms of potential network externalities (Table 4).

To summarize, while the comparison of our sample with the ICObench one unearths, as expected, some selection, we believe differences are not large enough to invalidate our analysis or undermine its external validity. Two more related aspects should be taken into consideration. First, selection (and self-reporting) issues are common in datasets that cover private capital markets, including VC deals, because of opaqueness due to lack of mandatory reporting. Second, some positive selection most likely rids our sample of ventures of dubious merit that take advantage of the lack of regulatory oversight offered by cryptocurrency markets. Therefore, given the increasing number of regulatory interventions in the decentralized finance space, our sample may resemble more closely the ICO market going forward. Consistently with this view, ICOs in our sample are almost evenly split

[19]Lee et al. [2019] show that use of bonus schemes and KYC verification is associated with less success in fund raising

between year 2017 (50%) and year 2018 (48%) while the vast majority of ICOs in ICObench (73%) take place in 2018, year that marked the peak of the ICO hype and that presumably saw, like for the IPO wave during the dotcom bubble, a deterioration in the quality of issuers (Table 6a). Additionally, companies in our dataset are more likely to be located in USA, Singapore, Russia and Switzerland, countries where regulators are have been more active in increasing their oversight, while allowing the market to operate (Table 6b).

6 VC vs ICO

In Section 4 we establish testable predictions on two sets of empirical relationships. The first is the relationship between startup's funding method and deal flow, that is the composition and characteristics of entrepreneurs that choose to engage with one market or the other. The second is the relationship between funding method and outcome sensitivity to externality effects. In what follows we examine these relationships and discuss additional relevant empirical patterns and possible limitations of our analysis.

6.1 Deal Flow

The ultimate *raison d'être* of the VC industry is to connect new ventures in search for funds with households (and intermediaries investing on behalf of households, e.g. pension funds) looking for profitable investment opportunities. Intermediation is necessary due to information limitation and regulatory constraints that prevent startups from offering securities directly to the general public.

Technology and innovation change this paradigm. With ICOs, firms can advertise their funding campaign freely online and reach out to final investors. This, however, does not necessarily imply that that the pool of firms that seek funding through an ICO is qualitatively similar to that of firms resorting to VC finance. Additionally to the benefits of leveraging network effects, ICOs allow founders to fund themselves without equity commitment or with very limited, if any, loss of control on business operations. This makes token-based finance attractive for entrepreneurs who value control and autonomy (Moskowitz and Vissing-Jørgensen [2002], Hamilton [2000]). Moreover, the advantage of ICOs resides in the possibility of reaching a larger investors base faster than it would be otherwise possible because of regulatory or transaction limitations, which suggests that deal flow composition may depend on firm jurisdiction. To examine differences in deal flow composition, we explore round and firm characteristics associated with token issuance.

In Table 7 we regress a dummy variable that takes value 1 if the focal firm ever raises capital with an ICO. Columns 1 and 2 show results of a linear probability model estimation while column 3 shows coefficients of a probit model. Firms that issue tokens are less likely to be located in North America, where traditional entrepreneurial funding methods such as Angel or VC finance are more widely available. Moreover, token issuers seem to have more experienced founders team and to be marginally older at the time of their first financing event. These patterns persist unchanged in significance and magnitude when we add team level controls (columns 2 and 3).

Finally, as predicted by our model, ICOs are strongly associated with the presence of potential network externalities, as measured by our externality index $Externality$. Using both linear and probit models, an increase of one unit in the externality index increases the probability of using ICO as a funding method by approximately 6%.

6.2 Funding Methods, Outcomes and Externality Effects

Before examining outcome sensitivity to externality effects, we offer some preliminary evidence on the relationship between funding method and outcomes in Table 8 . In the absence of accounting measures of revenues or profits, which would match better the concept of outcome in our model, we draw from previous entrepreneurial finance literature and measure outcomes as 1) $Employment$, a dummy variable that takes value 1 if the firm has more than 10 employees and 2) $Web\,Traffic$, a variable that equals the natural logarithm of the average monthly visits to the firm's website.[20] The explanatory variable ICO takes value one if the firm ever issues tokens, regardless of whether ICO is the only funding type or it is used jointly with VC. Since outcomes are measured at a fixed date (June 2019) we control for age of the firm at first round and we add year of first round fixed effects to account for firms' maturity at the measurement date.

Token issuers appear to achieve better employment outcomes (column (1)). However, these

[20] Employment is a common measure of outcomes in VC studies, see for example Puri and Zarutskie [2012]. Web traffic has been used in previous studies in entrepreneurial finance, see for example Kerr et al. [2011]

effects seem to be due to the larger amounts of capital raised, as the coefficient on ICO becomes insignificant when we control for total funding (column (2)). This result is interesting in that it suggests that employment growth is affected by the size of capital injections but not by investors type.

Differently from employment, web traffic robustly depends on funding type, even when we control for total funding (columns (3) and (4)). Token issuers websites have roughly 130,000 more monthly visits. As expected, other relevant determinants are total number of financing events and team size. Moreover, the interaction between ICO and a dummy variable that takes value one if the firm was older than one year at the time of its first funding round is negative and significant (column (5)). In other words, effects are stronger for firms that access ICO funding in their very early stages, when public attention is presumably at its minimum. This suggests that, although we can not use changes in web traffic over time as our dependent variable due to data limitations, we are effectively picking up differences in growth rates rather than levels.

Observed differences in outcomes may arise because of differences in the quality of the deal flow in the two markets. In this case, we should observe stronger effects in places, like North America, where entrepreneurial finance markets are more developed and firms effectively have the possibility of choosing either decentralized or traditional funding methods like VC. Our empirical findings do not support this view as the interaction term between ICO and a dummy variable that takes value one if the firm is located in North America is not statistically significant (column (6)). Said differently, the outcomes associated with decentralized finance are similar across firm locations.

Based on this preliminary evidence alone, it appears that token-based finance offers some advantages with respect to traditional entrepreneurial finance as it allows entrepreneurs to raise more funds, it does not negatively affect employment growth, and it correlates with stronger web traffic growth. We interpret these facts as evidence that the benefits of token-based finance, such as network externality effects, are at least comparable, in terms of impact on outcomes, to VC's monitoring/advising activities. Therefore, cryptocurrency markets can contribute to entrepreneurial finance in a non-trivial manner, providing legitimacy to researchers' interest in this novel area.

Next, we test the model predictions regarding the effect of externality on outcomes. In Table

9, column 1, we show that projects that receive ICO funding in their first round are significantly less likely to receive follow-on capital. Moreover, output is increasing in network externality only for projects financed with ICOs, whether alone or in combination with VC, but not for project financed with VC only (column 2). This evidence supports our main theoretical result, namely that entrepreneurs who opt for VC-only funding forsake externality gains altogether in order to avoid adverse selection in follow-on rounds thus increasing the probability of receiving additional capital further down the line.

Finally our model implies that, in presence of adverse selection, larger externality effects on output for projects funded with both ICO and VC can only arise in presence of complementarities between the two funding methods. This is because startups that do not raise additional funding after an ICO, "$ICO - Only$" firms, are better in terms of entrepreneurial ability than startups that use both sources, "$ICO - VC$" firms. It follows that, if outcomes of "$ICO - VC$" firms are more sensitive to externality effects it must be so by virtue of the interaction between VC contribution to profitability (h) and the customer base N, which increases with network effects. In Table 9, column 3 we show that this is indeed the case, as the coefficient for the interaction variable $ICO - VC \times Externality$ is significantly larger than that for the interaction variable $ICO - Only \times Externality$.

Our theoretical and empirical results show that network externalities are a fundamental force behind the use of cryptocurrency in the context of entrepreneurial finance, and that more transparency may be required for this market to contribute to business dynamism. Before concluding, two considerations are in order. The first is that our sample consists of companies operating in business areas that allow for the use of blockchain technologies. While this leaves the question open of whether similar results apply to different types of companies, our conceptual framework does not rely on the specificities of blockchain infrastructues and our evidence remains informative of current evolution in the financial system, especially in light of the possibility that blockchain technologies become more and more pervasive in our economies. The second consideration is that, while we focus on network externalities, other features of ICO funding may be attractive for entrepreneurs, such as demand discovery (Catalini and Gans [2018]) and retention of control (Howell et al. [2018],Chod and Lyandres [2018]). We leave an empirical investigation into these issues for future research.

7 Conclusions

In recent years, information technology and computer science have widely revolutionized financial intermediation, with implications, in terms of efficiency and stability of the financial (and real) sector, that are yet to be understood. Advocates of blockchain-based decentralized finance argue that, by "disintermediating" financial transactions, DeFi is effective in fostering wider global accessibility to financial services, safer transactions, and lower costs. It is no surprise that the impetus for (and the interest surrounding) FinTech innovations came at a time when, after the latest financial crisis, there is a growing belief that the global financial system is inefficient and it contributes to numerous inequalities. Can technology disrupt rent seeking behavior of financial intermediaries, improving common welfare? Answering this question requires a cost-benefit analysis of "old" versus "new" methods, and our paper attempts to perform this exercise in the context of entrepreneurial finance. In particular we compare cryptocurrency funding with established funding channels, such as Venture Capital.

We propose a model of staged finance where entrepreneurs can choose between ICO and VC funding. Differently from traditional VC funding, ICOs allow firms to build a large initial customer base and exploit network externality effects in early stages. This is possible because of ICO subscribers' double nature of both investors and (potential) product users. Additionally, positive externality effects can be hastened by VC's active involvement in firm management through monitoring and advising services, thus further improving firm outcomes in later stages. That is, VC capital can complement token-based finance. Despite the benefits of using both funding sources sequentially, however, lack of transparency and regulatory oversight in cryptocurrency markets can limit the extent to which startups take full advantage of the complementarity between ICO and VC finance, thus inducing sub-optimal funding choices. In particular, our model results in a selection equilibrium where entrepreneurs with low-externality projects choose to forsake complementarity benefits and raise VC capital only, in order to avoid underpricing in later stages.

We provide empirical evidence for our theoretical results using data on global startups funding events, firm characteristics and measures of output. In particular we find that firms that use ICO funding are characterized by a higher level of network externality effects. Moreover, for firms that use VC funds in initial rounds access to follow-on capital is more likely while the sensitivity of outputs to externality is muted, supporting the rationale for selection proposed in our model.

Our findings are consistent with the view that decentralized finance can alleviate firms' financial constraints and it can effectively complement traditional entrepreneurial finance methods. Fostering transparency in cryptocurrency markets, for example via mandatory disclosure requirements or adoption of self-regulatory standards, allows firms to better exploit the benefits of the interaction between old and new entrepreneurial finance.

References

Anat Admati and Paul Pfleiderer. Robust financial contracting and the role of venture capitalists. *Journal of Finance*, 49(2):371–402, 1994.

Natee Amornsiripanitch, Paul A Gompers, and Yuhai Xuan. More than money: Venture capitalists on boards. *Available at SSRN 2586592*, 2017.

Yannis Bakos and Hanna Halaburda. The role of cryptographic tokens and icos in fostering platform adoption. 2019.

Dirk Bergemann and Ulrich Hege. Venture capital financing, moral hazard, and learning. *Journal of Banking & Finance*, 1998.

Bruno Biais, Christophe Bisiere, Matthieu Bouvard, Catherine Casamatta, and Albert J Menkveld. Equilibrium bitcoin pricing. *Available at SSRN 3261063*, 2018.

Nicola Borri and Kirill Shakhnov. Cryptomarket discounts. *Available at SSRN 3124394*, 2019.

Greg Buchak, Gregor Matvos, Tomasz Piskorski, and Amit Seru. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3):453–483, 2018.

Christian Catalini and Joshua S Gans. Initial coin offerings and the value of crypto tokens. Technical report, National Bureau of Economic Research, 2018.

Jiri Chod and Evgeny Lyandres. A theory of icos: Diversification, agency, and information asymmetry. *SSRN Working Paper*, 2018.

Stijn Claessens, Jon Frost, Grant Turner, and Feng Zhu. Fintech credit markets around the world: size, drivers and policy issues. *BIS Quarterly Review September*, 2018.

Lin William Cong, Ye Li, and Neng Wang. Tokenomics: Dynamic adoption and valuation. *Becker Friedman Institute for Research in Economics Working Paper*, (2018-49):2018–15, 2019.

Tetiana Davydiuk, Deeksha Gupta, and Samuel Rosen. De-crypto-ing signals in initial coin offerings: Evidence of rational token retention. *Available at SSRN 3286835*, 2019.

Calebe De Roure, Loriana Pelizzon, and Anjan V Thakor. P2p lenders versus banks: Cream skimming or bottom fishing? 2019.

Jon Frost, Leonardo Gambacorta, Yi Huang, Hyun Song Shin, and Pablo Zbinden. Bigtech and the changing structure of financial intermediation. 2019.

Lawrence R Glosten and Paul R Milgrom. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 1985.

Paul A. Gompers. Optimal investment, monitoring, and the staging of venture capital. *The Journal of Finance*, 50(5):1461–1489, 1995. doi: 10.1111/j.1540-6261.1995.tb05185.x.

Paul A Gompers, Will Gornall, Steven N Kaplan, and Ilya A Strebulaev. How do venture capitalists make decisions? *Journal of Financial Economics*, 2019.

Sanford J Grossman and Joseph E Stiglitz. On the impossibility of informationally efficient markets. *The American Economic Review*, 1980.

Barton H Hamilton. Does entrepreneurship pay? an empirical analysis of the returns to self-employment. *Journal of Political Economy*, 2000.

Thomas Hellmann and Manju Puri. Venture capital and the professionalization of start-up firms: Empirical evidence. *The Journal of Finance*, 57(1):169–197, 2002.

Sabrina T Howell, Marina Niessner, and David Yermack. Initial coin offerings: Financing growth with cryptocurrency token sales. Technical report, National Bureau of Economic Research, 2018.

Albert Hu, Christine A Parlour, and Uday Rajan. Cryptocurrencies: Stylized facts on a new investible instrument. *Available at SSRN 3182113*, 2018.

Steven N. Kaplan and Per Stromberg. Financial contracting theory meets the real world: An empirical analysis of venture capital contracts. *Review of Economic Studies*, 70(2):281–315, 2003.

Michael L Katz and Carl Shapiro. Network externalities, competition, and compatibility. *American Economic Review*, 1985.

Michael L Katz and Carl Shapiro. Technology adoption in the presence of network externalities. *Journal of political economy*, 94(4):822–841, 1986.

William R Kerr, Josh Lerner, and Antoinette Schoar. The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, 2011.

Albert S Kyle. Continuous auctions and insider trading. *Econometrica*, 1985.

Jeongmin Lee and Christine A Parlour. Crowdfunding, initial coin offerings, and consumer surplus. *Available at SSRN 3300297*, 2018.

Jongsub Lee, Tao Li, and Donghwa Shin. The wisdom of crowds in fintech: Evidence from initial coin offerings. *Available at SSRN 3195877*, 2019.

Josh Lerner. Venture capitalists and the oversight of private firms. *The Journal of Finance*, 50(1): 301–318, 1995.

Jiasun Li and William Mann. Initial coin offerings and platform building. 2018.

Simon Mayer. Token-based platforms and speculators. *Available at SSRN 3471977*, 2019.

Tobias J Moskowitz and Annette Vissing-Jørgensen. The returns to entrepreneurial investment: A private equity premium puzzle? *American Economic Review*, 2002.

Stewart C Myers and Nicholas S Majluf. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 1984.

Thomas Philippon. The fintech opportunity. *NBER Working Paper*, 2016.

Manju Puri and Rebecca Zarutskie. On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms. *The Journal of Finance*, 2012.

Linda M. Schilling and Harald Uhlig. Currency substitution under transaction costs. *AEA Papers and Proceedings*, 109:83–87, May 2019. doi: 10.1257/pandp.20191017. URL `http://www.aeaweb.org/articles?id=10.1257/pandp.20191017`.

Michael Sockin and Wei Xiong. A model of cryptocurrencies. *Unpublished manuscript, Princeton University*, 2018.

Morten Sørensen. How smart is smart money? a two-sided matching model of venture capital. *The Journal of Finance*, 62(6):2725–2762, 2007.

Anjan V Thakor. Fintech and banking: What do we know? *Journal of Financial Intermediation*, 2019.

Xuan Tian. The causes and consequences of venture capital stage financing. *Journal of Financial Economics*, 101(1):132–159, 2011.

Gerry Tsoukalas and Brett Hemenway Falk. Token-weighted crowdsourcing. *The Wharton School Research Paper*, 2018.

Susheng Wang and Hailan Zhou. Staged financing in venture capital: moral hazard and risks. *Journal of Corporate Finance*, 10(1):131–155, 2004.

Table 1: Firm Location

	Obs.	%	Cum%
United States	408	34.06	34.06
European Union (Ex UK)	161	13.44	47.50
Other	119	9.93	57.43
United Kingdom	116	9.68	67.11
China	89	7.43	74.54
Singapore	74	6.18	80.72
Switzerland	52	4.34	85.06
Canada	40	3.34	88.40
Hong Kong	34	2.84	91.24
India	22	1.84	93.07
Israel	21	1.75	94.82
Australia	18	1.50	96.33
Gibraltar	17	1.42	97.75
Russian Federation	16	1.34	99.08
Cayman Islands	11	0.92	100.00
Total	1198	100.00	

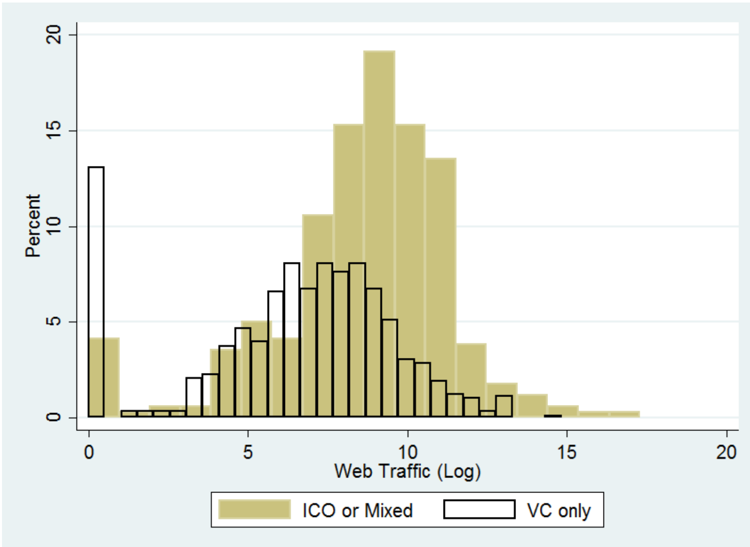
Notes: The table provides the geographical location of firms in our sample across the world. The category "Other" aggregates all countries that have ten issuers or less . Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Table 2: Firm Characteristics, Funding Choices and Outcomes

	Mean	Median	Min	Max	Obs
Team Size	2.10	2.00	1.00	8.00	1007
Females in Team	0.07	0.00	0.00	1.00	1007
Team News	3.61	0.00	0.00	357.50	1007
Team Experience	1.44	1.00	0.00	9.00	1007
Team Exits	0.04	0.00	0.00	12.00	1007
Top School in Team	0.17	0.00	0.00	1.00	1007
Mixed Funding	0.12	.	.	.	1218
ICO only	0.16	.	.	.	1218
VC only	0.72	.	.	.	1218
10+ Employees	0.43	.	.	.	1218
Web Traffic	59299.55	1991.61	0.00	32480362.76	1218

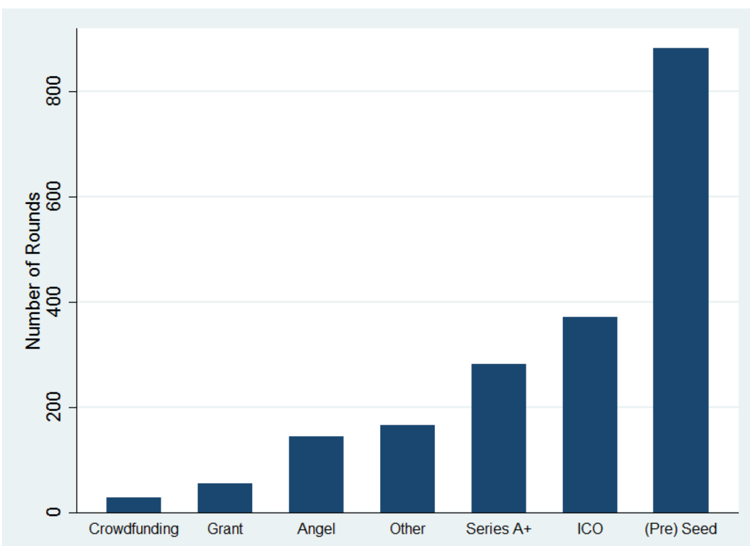
Notes: The table illustrates firm characteristics: Team size (the number of team members); Females in Team (the share of females in teams in %); Team News (number of articles referring to the founder); Team Experience (the number of companies founded by team members, including the current one); Team Exits; Top School in Team (the percentage of team members, who attended a top school); and Web Traffic (average number of monthly visits measured as of June 2019). We also report the fraction of sizeable firms with more than ten employees, and the fraction of firms, relying on ICO only, VC only, or Mixed funding. Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Figure 1: Web Traffic by Funding Type



Notes: This figure presents the histograms of Web Traffic(average number of monthly visits measured as of June 2019). The solid golden-green bars represent the funding cases, which include ICO, such as ICO or Mix funding. The transparent bars represent VC only funding. Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Figure 2: Rounds by Funding Type



Notes: The bar plot presents the number of funding rounds depending on funding types. We observe almost 400 ICOs in our sample. Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Table 3: Round Characteristics

(a) ICO rounds

	Mean	Median	Min	Max	Obs
Amount	33.18	11.00	0.01	4000.00	289
Firm Age(days)	437.75	376.50	0.00	1488.00	366
Num Investors	2.55	1.00	1.00	13.00	112
Step Up	21.70	1.11	0.00	500.00	28
Days to Next Round	218.60	105.50	1.00	2414.00	80

(b) Non ICO rounds

	Mean	Median	Min	Max	Obs
Amount	4.93	0.76	0.00	1000.00	1022
Firm Age (days)	437.30	396.00	0.00	1596.00	1519
Num Investors	2.44	1.00	0.00	23.00	1035
Step Up	9.06	2.49	0.00	206.82	340
Days to Next Round	228.02	181.00	1.00	1460.00	633

Notes: The table provides information about round characteristics: Amount in millions of US dollars; Firm Age in days; Num Investors (the number of investors); Step Up (a capital injection in millions of US dollars in the followup round), the number of days till the next round. Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Table 4: ICObench vs Crunchbase: Continuous Variables

(a) ICObench

	Mean	Median	Min	Max	Obs
Team	12.86	11	1	73.00	3452
Rating	2.99	3	1	4.90	3736
Media	5.98	6	0	10.00	3736
Amount	11.94	4	0	1700.00	1044
Distributed	56.29	58	0	100.00	2762
ICO Duration	60.04	40	0	1826.00	2868
Externality Index	1.19	1	0	7.00	3736

(b) Crunchbase

	Mean	Median	Min	Max	Obs
Team	15.72	15	1	49.00	343
Rating	3.34	3	1	4.70	351
Media	6.50	7	0	10.00	351
Amount	36.20	12	0	4197.96	291
Distributed	50.66	50	6	100.00	213
ICO Duration	44.66	30	0	760.00	287
Externality Index	1.12	1	0	6.00	351

Notes: The table provides information about firm characteristics for two ICObench subsamples. We call Crunchbase the subsample, which is matched with Crunchbase. We call ICObench the remaining subsample, which is unmatched with Crunchbase. Team is the number of team members. Rating is the rating of ICO provided by ICObench. The rating algorithm evaluates the team's expertise, availability of information and transparency, media presence, and marketing material. Experts' ratings are weighted by contributors' expertise, years of experience in the field, and possible available publications. Media measures media presence, i.e., the number of channels through which the company advertises its project (e.g., Twitter, GitHub, Facebook, etc.). Amount raised on ICO is in millions of US dollars. Distributed stands for the proportion of tokens distributed to the public (rather than retained by the firm managers). Externality index is the number of times Network Keywords are mentioned in each company's short business description. Network Keywords are Gaming, Communities, Platform, Messaging, Open Source, Auction, Portals, Exchange, Developer, Collaboration, Delivery, Peer, Network, Marketplace. While Panel (a) at the top presents data from ICObench https://www.icobench.com, panel (b) presents data data from https://www.crunchbase.com. Data are for the period 1/1/2015–1/6/2019.

Table 5: ICObench vs Crunchbase: Binary Variables

	(1) ICObench Mean	Obs.	(2) Crunchbase Mean	Obs.
Exchange Info	0.162	3736	0.510	351
Bonus	0.453	3736	0.368	351
Fiat Accepted	0.112	3736	0.114	351
PreICO	0.505	3736	0.402	351
Roadmap	0.886	3736	0.815	351
KYC>0	0.580	3736	0.473	351
Hardcap	0.706	3736	0.632	351
Softcap	0.541	3736	0.362	351
Observations	3736		351	

Notes: TThe table provides information about ICOs for two ICObench subsamples. We call Crunchbase the subsample, which is matched with Crunchbase. We call ICObench the remaining subsample, which is unmatched with Crunchbase. The table reports the proportions of ICOs for which the information about exchanges for future ICO listing was provided. The table also reports whether pre-ICO was conducted; bonus schedule was offered; fiat currencies were accepted in exchange for tokens; if hardcap or softcap were set; if company's plan for future development and funding ("roadmap") was available; whether any of the team members passed a KYC verification procedure. Data are from https://www.crunchbase.com and https://www.icobench.com for the period 1/1/2015–1/6/2019.

Table 6: ICObench vs Crunchbase: Timing and Location

(a) ICO Year

	ICObench %	Crunchbase %	Total %
2015	0.07	0.00	0.06
2016	0.56	1.32	0.63
2017	25.32	50.66	27.61
2018	73.00	47.68	70.72
2019	1.05	0.33	0.99
Total	100.00	100.00	100.00

(b) Firm Location

	ICObench %	Crunchbase %	Total %
Europe	26.39	19.66	25.81
NA	3.51	0.85	3.28
North America	16.27	24.50	16.98
Other	24.09	20.23	23.76
Russia	6.96	7.98	7.05
Singapore	9.07	11.68	9.30
Switzerland	4.79	7.69	5.04
UK	8.91	7.41	8.78
Total	100.00	100.00	100.00

Notes: The table compares across time and geographical locations two ICObench subsamples. We call Crunchbase the subsample, which is matched with Crunchbase. We call ICObench the remaining subsample, which is unmatched with Crunchbase. Total stands for the whole ICObench sample. While panel (a) at the top presents data over time, panel (b) presents data across geographical locations. Data are from https://www.crunchbase.com and https://www.icobench.com for the period 1/1/2015–1/6/2019.

Table 7: Firm Characteristics and ICO

	(1)	(2)	(3)
Externality	0.0572***	0.0622***	0.1784***
	(0.0200)	(0.0224)	(0.0664)
Age at 1st Round	0.0001**	0.0001**	0.0004**
	(0.0000)	(0.0001)	(0.0002)
NorthAmerica	-0.1401***	-0.1590***	-0.5972**
	(0.0529)	(0.0568)	(0.2682)
Team %Female		-0.0280	-0.1056
		(0.0671)	(0.2090)
Team News		-0.0003	-0.0009
		(0.0008)	(0.0021)
Team Experience		0.0441**	0.1267**
		(0.0196)	(0.0549)
Team Top School		-0.0179	-0.0515
		(0.0472)	(0.1396)
# Founders		-0.0015	-0.0044
		(0.0127)	(0.0387)
1st Round-Year FE	Yes	Yes	Yes
N	1175	967	967
adj. R^2	0.062	0.055	
pseudo R^2			0.058

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports cross-sectional regressions for a dummy variable that takes value of one if the funding round is an ICO and zero otherwise. The table reports cross-sectional regressions for a dummy variable that takes the value of one if the funding round is an ICO and zero otherwise. Columns (1) and (2) are linear probability models (OLS). Column (3) presents the results of Probit estimations. Standard Errors are in parentheses. All specifications include the first round fixed effect. The regressors are: externality index; age at the first round; the North American dummy; the share of females in teams in % (Team % Female); the number of articles referring to the founder (Team News); the number of companies founded by team members, including the current one (Team Experience); the percentage of team members, who attended a top school (Team Top School); the number of founders (Founders). The externality index is the number of times Network Keywords are mentioned in each company's short business description. Network Keywords are Gaming, Communities, Platform, Messaging, Open Source, Auction, Portals, Exchange, Developer, Collaboration, Delivery, Peer, Network, and Marketplace.

Table 8: Funding Method and Outcomes

	(1) Employment	(2) Employment	(3) Web Traffic	(4) Web Traffic	(5) Web Traffic	(6) Web Traffic
ICO	0.2180***	0.0216	1.7921***	0.7951***	1.0852***	0.8065***
	(0.0350)	(0.0450)	(0.1862)	(0.2105)	(0.2476)	(0.2130)
Ln(Tot. Rounds)	0.0804**	0.0089	1.5721***	1.0481***	1.0495***	1.0479***
	(0.0371)	(0.0394)	(0.2026)	(0.2114)	(0.2115)	(0.2113)
Ln(# Founders)	0.0571*	0.0621*	0.9888***	0.9242***	0.9327***	0.9266***
	(0.0313)	(0.0339)	(0.1711)	(0.1749)	(0.1747)	(0.1751)
Team Experience	-0.0298	-0.0310	-0.0154	-0.0797	-0.0805	-0.0809
	(0.0216)	(0.0240)	(0.1204)	(0.1195)	(0.1189)	(0.1193)
Age	-0.0000	-0.0001**	0.0007**	0.0001	0.0005	0.0001
	(0.0001)	(0.0001)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
NorthAmerica	-0.0512	-0.1338	0.3055	0.3582	0.3685	0.4856
	(0.0799)	(0.1022)	(0.4461)	(0.4661)	(0.4644)	(0.5562)
Ln(Tot. Amount)		0.1443***		0.7691***	0.7641***	0.7708***
		(0.0176)		(0.0815)	(0.0813)	(0.0816)
ICO X Age>1yr					-0.7008**	
					(0.3211)	
ICO X NorthAmerica						-0.7088
						(0.7268)
Round-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	967	740	967	740	740	740
adj. R^2	0.058	0.163	0.180	0.274	0.277	0.273

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the results of OLS regressions for outcome variables. Columns (1) and (2) are for Employment. Columns (3)-(6) are for Web Traffic. Standard Errors are in parentheses. All specifications include the round-year fixed effect. Employment is a dummy variable that takes value one if the firm has more than 10 employees. Web Traffic is the natural logarithm of the average monthly visits to the firm's website measured as of June 2019. The regressors are: an ICO dummy, which takes value one if the firm ever issues tokens; the number of rounds in logs (Ln(Tot. Rounds)); the number of founders in logs (Ln(Founders)); the number of companies founded by team members, including the current one (Team Experience); the age of the firm at first round (Age); the North American dummy; the total amount of capital raised in logs (Ln(Tot. Amount)); the interaction term of the ICO dummy with a dummy variable that takes value one if the firm was older than one year at the time of its first funding round; the interaction term of the ICO dummy with the North American dummy.

Table 9: Funding Method,Outcomes, and Externality Effects: Mixed Funding vs ICO-only

	(1) Follow-On	(2) Web Traffic	(3) Web Traffic
ICO 1st Round	-0.1665***		
	(0.0439)		
ICO X Ext.		0.7196***	
		(0.2169)	
VC only X Ext.		0.2648	0.2667
		(0.1817)	(0.1819)
ICO&VC X Ext.			0.9497***
			(0.3191)
ICO only X Ext.			0.5426*
			(0.2884)
ICO		0.8200***	
		(0.2698)	
ICO only			1.1149***
			(0.3649)
ICO&VC			0.4296
			(0.3105)
Ln(Amt)	-0.0034		
	(0.0168)		
Age	-0.0001**	0.0002	0.0002
	(0.0001)	(0.0004)	(0.0004)
NorthAmerica	-0.1273	0.6937	0.7069
	(0.0830)	(0.4931)	(0.4964)
Ln(Tot. Rounds)		1.4068***	1.5496***
		(0.2121)	(0.2538)
Ln(Tot. Amount)		0.7320***	0.7351***
		(0.0861)	(0.0857)
Round-Year FE	Yes	Yes	Yes
N	806	886	886
adj. R^2	0.152	0.247	0.247

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the results of OLS regressions for Follow-on and Web traffic. Columns (1) is for Follow-on. Columns (2) and (3) are for Web Traffic. All specifications include the round-year fixed effect. Follow-on is a dummy variable, which takes value one if the firm has a follow-on round. Web Traffic is the natural logarithm of the average monthly visits to the firm's website measured as of June 2019. The regressors are: an ICO first-round dummy, which takes value one if the firm issues tokens as the first funding round; the age of the firm at first round (Age); the North American dummy; the amount of capital raised in a funding round in logs (Ln(Amount)); the total amount of capital raised in all funding round in logs (Ln(Tot. Amount)); the number of rounds in logs (Ln(Tot. Rounds)). Additional regressors for Columns (2) and (3) are three dummy variables and their interaction terms with the externality index. The dummy variables are: ICO dummy takes value one if the firm ever issues tokens; ICO only dummy takes value one if a firm relies exclusively on an ICO; ICO & VC dummy takes value one for mixed funding firms. The externality index is the number of times Network Keywords are mentioned in each company's short business description. Network Keywords are Gaming, Communities, Platform, Messaging, Open Source, Auction, Portals, Exchange, Developer, Collaboration, Delivery, Peer, Network, and Marketplace.

Appendix A

Suppose the entrepreneur chooses ICO in the first stage. At $t = 0$, the payoff for ICO investors contributing K is

$$Y_0^{ICO} = q_1^{ICO} E_0^{ICO} \left[U \left(V \right) \right] - K$$

where $U \left(\cdot \right)$ is ICO investor utility function and $E_0^{ICO} \left[U \left(V \right) \right]$ is the expected utility of firm value V. We derive the equilibrium share by setting Y_0^{ICO} equal to invetsors' outside option, zero. Thus

$$q_1^{ICO} = \frac{k_1}{E_0^{ICO} \left[U \left(V \right) \right]}$$

To model risk aversion we change probability measure and use risk-neutral probability $\dot{p}$ instead of natural probability p. If $\omega^H > \omega^L + h$ ($\omega^H < \omega^L + h$) any $\dot{p} \leq p$ ($\dot{p} \geq p$) guarantees $E \left(V \right) > E \left[U \left(V \right) \right]$, thus risk aversion.We define $E_0^{ICO} \left[U \left(V \right) \right] = \tilde{z} N$ where $\tilde{z} = \dot{p} \omega^H + \left(1 - \dot{p} \right) \left(\omega^L + h \right) < p \omega^H + \left(1 - p \right) \left(\omega^L + h \right) \equiv \check{z}$.

Given optimal strategies in stages one and two, entrepreneurs' expected utility is

$$= \check{z} N - K \frac{\check{z}}{\tilde{z}} - \left(1 - p \right) \kappa$$

Entrepreneurs receive the expected value of the project ($\check{z} N$) net of investors' expected compensation. In ICO first rounds capital is more expensive than in VC rounds because of risk aversion (i.e. $\frac{\check{z}}{\tilde{z}} \geq 1$).

ICO is preferred if the following condition holds

$$f \left(\varepsilon \right) = \mathit{\Phi} \left(\alpha \right) \left(\bar{z} \right)^{\frac{1}{1-\alpha}} \left[\mu^{\frac{\varepsilon}{1-\alpha}} \frac{\check{z}}{\bar{z}} \left(\frac{\tilde{z}}{\bar{z}} \right)^{\frac{\alpha}{1-\alpha}} - 1 \right] + p \kappa \geq 0$$

where $\mathit{\Phi} \left(\alpha \right) = \alpha^{\frac{1}{1-\alpha}} \left(\alpha^{-1} - 1 \right)$.

Intuitively, investors risk aversion makes ICO funding less attractive for entrepreneurs.

Appendix B

With $\underset{\alpha \to 0}{lim} \Phi(\alpha) = 1$ we have

- $\underset{\alpha \to 0}{lim} \bar{\kappa} = h$
- $\underset{\alpha \to 0}{lim} \underline{\kappa} = \frac{\bar{z}}{\bar{z}+(1-p)\Delta} \frac{1}{\mu^{\varepsilon} h}$

and

- $\underset{\alpha \to 1}{lim} \bar{\kappa} = \infty$
- $\underset{\alpha \to 1}{lim} \underline{\kappa} = 0$

which implies that $\bar{\kappa} > \underline{\kappa}$ at least in some interval of the support of α. Also notice that with $\mu \to \infty$ $\underline{\kappa} = 0$ $\forall \alpha \in (0;1)$. Since $\bar{\kappa} > 0$ $\forall \alpha \in (0;1)$ it follows that there exist μ^* such that if $\mu > \mu^*$then $Max[\underline{\kappa}] < Min[\bar{\kappa}]$ $\forall \alpha \in (0;1)$. In other words, when μ is sufficiently large the equilibrium result is independent of α.