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Abstract

We propose a model of entrepreneurial finance where start-ups raise capital via Initial Coin Offering (ICO) or traditional funding methods such as Venture Capital (VC). While token sales allow startups to leverage network effects, VC's value-adding services enhance product quality. We show that, even when projects have large potential network effects, ICOs may not be optimal if entrepreneurial ability is low. Moreover, despite the potential complementarity between network effects and value-adding services, entrepreneurs combine VC and ICO funding only in highly efficient VC markets and for projects with high network effects. Using data on funding rounds of blockchain startups, we empirically validate the main results of the model.

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

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 dropped dramatically from its peak in early 2018 and then partially recovered afterwards (to approximately $2 billion in 2021), leaving investors wondering whether or in what form ICO fundraising will be relevant going forward.

To answer this question, we examine the possible drivers of entrepreneurs' choice between ICO and traditional funding methods for startups, like Venture Capital (VC). We start by providing some novel descriptive evidence using data on global startup funding events, firm characteristics, and outcome measures. We find that ICO funding is more common among firms with projects that benefit from network effects, i.e. projects where prospective customers are attracted by the size of the existing network of users (e.g. online gaming). However, ICOs are relatively rare among firms located in areas where VC capital markets are long established and well developed, regardless of potential network effects benefits. Finally, ICOs are not exclusively conducted with retail investors but are often subscribed by professional investors such as VCs. Accounting for these stylized facts, we propose a theoretical framework for entrepreneur's funding choices that builds on the trade-off between the specific comparative advantages offered by the two funding strategies. On the one hand, through the involvement of retail investors, ICOs help startups build large initial communties of users and leverage network effects. On the other hand, professional investors (like VCs) contribute to the improvement of firm outcomes through value-adding services.

The relationship between network effects and ICO funding has been explored by previous research on platform-based business, where the presence of many sellers and buyers on the platform reduces search costs and platform-specific tokens can facilitate adoption (see for example Li and Mann [2018], Cong et al. [2019], Sockin and Xiong [2018]). The benefits of network effects, however, may apply more generally to other business models where customers' valuation

[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.

of a service or product increases with the number of users (Katz and Shapiro [1986]). For example, social network platforms display network effects but are not primarily intended for matching buyers and sellers. Users of these services appreciate product qualities (such as the graphical interface and the simplicity of interaction with the application), but they also - or mostly - care about how many users are creating content or are active on the platform. In this example, crucial for the success of the business is the presence of consumers who are willing to actively engage with the community of users. Thus, in our model we propose a notion of network effects which is similar to Katz and Shapiro [1986] but emphasizes the role of *active* (vs *passive*) users. An active user engages with the community, for example by posting content on an online platform, generating positive externalities for other users. A passive user does not engage, but benefits from other people doing so. The decision to become active is modeled as a rational choice based on individual costs and benefits which are not perfectly observable by consumers ex-ante (i.e. before buying the product). Importantly, token-based funding can encourage consumers activism by providing retail investors with relevant information on the project during the product development phase. For example, firms may share information regarding their value proposition or their targets in terms of geographical or demographic reach and distribute provisional ("beta") versions of the product or service. Retail investors, who are also potential consumers, use this information to learn costs and benefits of engaging with other users *before* directly experiencing the product. Therefore, when informed consumers are more likely to be active users, ICO funding offers a way to leverage network effects at very early stages of the product life-cycle. Indeed, practitioners often refer to "community building" as one important advantage of ICO funding .

We juxtapose network effects provided by ICO funding with the benefits of professional investment. Contrary to retail investors who are dispersed and often remote from the firm, 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 recent evidence see Gompers et al. [2019]). Thus, due to the different nature of their respective comparative advantages, VC and ICO funding are not perfect substitutes, as each performs a specific role in enhancing firm's success. Hence, the two funding methods are potential complements, and, if possible, firms should seek an "optimal mix" of cryptocurrency and VC capital. This can be achieved, for example, with ICOs open to both retail and professional investors. In practice, our empirical evidence shows that while this "mixed" funding is not uncommon, many startups, including those with large potential network effects, do not diversify their funding sources away from traditional entrepreneurial finance. This suggests the presence of limitations to the advantages associated with crypto-finance. In our theoretical framework, we explore some of these possible limitations.

Our model features a cashless entrepreneur who relies on outside professional investors (VCs) or retail investors to raise capital for her business project. The investment takes place in the initial "funding" stage, while cash flows are realized in the subsequent "market" stage, when the new product (or service) becomes available to consumers. Using a decreasing returns to scale technology, capital is employed to generate the optimal amount of output units. Output price reflects consumers' utility from using the product, which depends on (exogenously given) entrepreneurial ability, on the total number of active users, and on the individual level of engagement. In particular, customers' valuation increase with entrepreneurial ability and with the total number of active users, but the second effect varies in intensity across products. In other words, projects are heterogeneous in the intensity of network effects. The benefits of active engagement, instead, depend on consumer's type. Owing to the novelty of the product, type is unknown to consumers unless they either experience the product directly or collect sufficient information on the project. We assume that this learning process requires one period to complete and that it is optimal for a user to be active only when she knows her type to be sufficiently *high*.

During the funding stage, the entrepreneur can raise funds exclusively with VC investors or through an ICO, which can be conducted with both retail and VC investors. With an ICO, the entrepreneur sells non-divisible digital claims - tokens - that, in the market stage, can be either redeemed for a unit of product or sold on a crypto-exchange. Thus, our model applies specifically to "utility" tokens, namely tokens that can be used as medium of exchange to purchase the company's product.[2] Crucially, ICO funding can provide a larger endowment of "active users", since some of the (retail) investors who become users also choose to actively

[2] For a discussion on additional token categorization see Section 2

engage with the community. This is so because consumers who directly invest in the project face lower costs of collecting information on the product as compared to other users, and can therefore learn their type in advance.

Differently from retail investors, professional VCs have no use value for the product and therefore do not contribute towards the formation of an initial users base. However, through their value-adding activities, VC investors can improve product quality beyond the level achieved though the founder's entrepreneurial ability alone. We assume that VC's effort in monitoring and advising is proportional to the share of total capital contributed (i.e. effort is proportional to VC's *skin-in-the-game*). In order to benefit from potential complementarities between network effects and value-adding services, the entrepreneur can combine retail and professional capital by conducting an ICO open to both investors types.

We compare entrepreneurial payoffs from the three options (ICO with retail investors only, VC-only round, or ICO with both investors types) to assess the optimality of each funding method in relation to the intensity of network effects and VC efficiency. Our main results are as follows. First, the presence of network effects is not a sufficient condition for ICO optimality. Rather, a high level of entrepreneurial ability is needed in order for token-based finance to emerge. This is because, when ability is low, entrepreneurial profits may decrease with network effects intensity, due to the negative feedback effects inherent in the token pricing mechanism. Intuitively, ICO token prices positively depend on expected product valuations. As network effects intensify, valuations, and, consequently, token prices increase. This however implies that, for any given amount of capital raised, the number of investors (and potential active users) shrinks. Thus, the relationship between entrepreneurial profits and network effects is positive only when the total amount of capital raised, i.e. the optimal scale of the project, is sufficiently large. In our model (as in previous ones, e.g. Evans and Jovanovic [1989]), the optimal scale of the project increases with entrepreneurial ability. Therefore, with ICO funding, profits increase in network effects only when entrepreneurial ability is high. This suggests that, in presence of alternative funding methods, ICOs are optimal only for a subset of firms.

Second, despite the potential complementarities between network effects and value-adding services, ICO funding with both retail and professional investors is optimal only in highly efficient VC markets. This is because VC investors crowd out potential product users from the investor pool, which reduces both network effects and VC's incentives to provide value-adding services. Overall, our model delivers a clear rationale for the co-existence of the three different funding methods, due to the heterogeneity in VC efficiency, project's network effects, and entrepreneurial ability.

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 effects based theories, and offer some early empirical evidence.[3] Moreover, as in Lee and Parlour [2018], Bakos and Halaburda [2019], Garratt and Van Oordt [2019],Catalini and Gans [2018],Malinova and Park [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 active 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. We illustrate data and relevant descriptive statistics in Section 3, and we present our empirical findings in Section 4. In Section 5, we present our model. In Section 6 we discuss some of our assumptions and their interpretations. Section 7 concludes.

[3] While we focus on network effects, other features of ICO funding may be attractive for entrepreneurs, such as demand discovery (Catalini and Gans [2018]), retention of control (Howell et al. [2018],Chod and Lyandres [2018]), seigniorage profits (Canidio [2020]).

2 An ICO primer

An Initial Coin Offering 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. ICO funding started around 2013, growing steadily in number of issues and volumes until 2018, when total capital raised reached almost 12 $ billion, a figure comparable with that of global early stage VC rounds. Volumes dropped substantially after 2018, but the market is still active in more recent times (see Figure 3). Some coins (like Bitcoin) are payment tokens, i.e. digital assets that can be used for storage of value and as currencies for transactions, while other 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" tokens.[4] Utility tokens -the ones our theory focuses on- do not usually grant any voting, board, redemption, liquidation, or residual cash flow right.[5]

Differently from VC deals which are typically negotiated behind closed doors, ICOs are advertised with the general public. Issuers disseminate an online document, the "whitepaper", that can vary in length (from a single page to close to one hundred) and content. Whitepapers 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, 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. Listing may not be necessary if tokens are intended to be traded OTC. Currently there exist over 300 crypto exchanges, which differ in trading volumes, range of currencies traded, and users/issuers fees. Thus, utility tokens ICOs resemble crowdfunding events, where entrepreneurs pre-sells their future output to a "crowd" of potential users, but also share the feature of tradability of the claims sold with equity issuances.

Cryptocurrency markets do not rely on central clearing authorities or financial intermediaries to validate trades and establish ownership. Instead, bookkeeping and settlement of transactions

[4] For an in depth discussion on token categorization see Cong and Xiao [2021]. For a theory of security and utility token funding mix optimality see Mayer [2019]

[5] 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.

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 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.[6] Most startups that use blockchain-based finance and cryptocurrencies also employ blockchain technologies for business purposes.

Due to its novelty and reliance on fast changing technologies, the crypto-fundraising market is in constant evolution. After the appearance of ICOs, this space has been populated by Security Token Offerings (where security tokens are sold directly on crypto exchanges), Initial Exchange Offerings (where tokens are offered with the support of a trading platform rather than on the company's website), and, in a more recent development, Initial DEX Offerings (where tokens are offered via a decentralized liquidity exchange).[7] Our model can apply to ICOs as well as new offering types to the extent that the digital claim sold can be classified as utility token.

3 ICOs and Start-up Funding: an Empirical Overview

3.1 Data

Our main data source is Crunchbase (CB), a commercial online platform that provides information about companies' funding rounds (conducted both in private and public capital markets), founding members and news. [8] 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, so that it is reasonable to assume that entrepreneurs managing these firms are familiar with blockchain technology, which is closely related to cryptocurrencies, and they

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

[7]See Lyandres et al. [2020] for empirical evidence on these market developments.

[8]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. 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

include ICOs as possible financing options to consider. Our dataset consists of 1,346 firms and 2,146 funding rounds.

Among all the funding rounds, 24% are Initial Coin Offerings. Other funding types are mostly seed and early-stage rounds (Figure 4). Table 1 shows descriptive statistics on rounds by funding type. ICOs are considerably larger than other rounds and the issuers are relatively older at the time of the funding event (columns 1 and 2). We also present information on whether CB records contain the number or the name of professional investors who participated in the funding round (column 3). Interestingly, at least 35% of ICOs are subscribed by professional investors, such as VCs, angels, or crypto-hedge funds. Therefore, ICOs are not purely crowd-funding events as they are not exclusively conducted with retail investors. Conditionally on being subscribed by professional investors, the average number of professional investors in ICOs is similar to that in (pre) seed rounds (2.6 versus 2.29, column 4).

At the firm level, we collect information on firm location and number of founders. We also collect information on founders' visibility on media outlets (i.e. number of articles referring to the founder) and experience (i.e. number of companies founded, including the current one), which we aggregate at the firm level.[9] Most firms are located in North America (35%), Europe (27%), China, Hong Kong, and Singapore (17% altogether) (Table 5). Table 2illustrates additional firm's characteristics and funding choices . The typical founding team comprises 2 members, with an average experience of 1.44 start-ups and media presence of 3.61 articles. Approximately 35% of firms in the sample raised capital with an ICO over the observation period.

Finally, we measure public "interest" in each firm in terms of web traffic (average number of monthly visits) as of June 2019. We interpret this measure as a proxy for consumers active engagement with the firm and its community. The average web traffic is almost 60 thousand visits per month, but the distribution is quite dispersed (see Figure 6, left panel). We also measure web traffic as of November 2021 (Figure 6, right panel). This information however is more sparse, as we obtain this data for less than half of the firms in our dataset. This is partly due to changes in companies names which prevents us from matching some of the firms in our

[9] 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.

initial sample with the current CB dataset, and partly due to the fact that, following a change in CB's provider of web traffic data, the current coverage is less comprehensive than when we initially started our data collection.

3.2 Measuring Potential Network Effects

We measure potential network externality for firms in our sample using simple textual analysis by the mean of natural language processing. Each firm in Crunchbase is associated with a short business description, that is one or two sentences describing the line of business in which the company operates. We identify Network Keywords, that is words that signal potentially large network effects (e.g. "network", "community", "platform"), and we construct our index of potential network externalities, $Network$, by counting the number of times Network Keywords are mentioned in each company's short business description. In our sample, 46% of firms exhibit positive potential network externalities. The $Network$ index ranges from 0 to 4 (with a mean of 0.58). [10]

We validate our measure using the sample of companies currently listed on the NASDAQ. In particular, we identify a group of firms that clearly exhibit network effects (e.g. Facebook). By means of a natural language processing algorithm, we verify that the business descriptions of companies in this group (as reported in official SEC filings and on online economic news outlets) include our Network Keywords significantly more frequently than the rest of the sample (see Internet Appendix, Section A).

3.3 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.[11] To investigate potential selection issues we collect information on the ICObench "universe" of ICOs and match ICOs in our dataset with records in ICObench, using website urls as identifiers. We leave the

[10] Network Keywords are: Game, Platform, Community, User, People, Connect, Group, Meet, Match, Messaging, Auction, Portal, Peer, Mining, Exchange Developer, Collaboration, Network, Marketplace. Descriptions comprise 12 words on average.

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

details of the matching procedure and its outcomes to the Internet Appendix (Section B). Here we limit ourselves to summarizing the results as follows. 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 as blogs or news outlets. Whether this is related to firm quality is less clear. For example, average differences in deal evaluations (as provided by ICObench.com) are remarkably small. Importantly, our sample does not differ from the ICObench.com "universe" in terms of potential network effects.

4 VC vs ICO: Empirical Evidence

In this section we present the results of two sets of regressions on funding methods, firm characteristics and web traffic, with the goal of exploring conditional correlations (of course, no causal statements can be inferred from this analysis). In Table 3 we analyze the relationship between firm characteristics and the funding method of choice by means of a simple linear probability regression model. The unit of analysis is the funding round. The outcome variable in columns 1 to 3 is a dummy variable that takes value 1 if the funding type is ICO and zero otherwise. In columns 4 we restrict the sample to ICOs only, and we set the outcome as a dummy variable that takes value 1 if the ICO is subscribed by professional investors, and zero otherwise. The independent variables include the *Network Index*, as described in Section 3.2. We also include firm age, founders team size, founders team experience, and founders team media presence as rough measures of entrepreneurial quality. Additionally, we use firm location as a proxy for VC efficiency. In particular, we introduce the binary variable *VC Hub* which takes value 1 if the firm is located in the Western US or New England, and zero otherwise. Therefore with this variable we identify firms located in areas such as Boston, San Francisco or San Jose, where traditional entrepreneurial funding methods such as Angel or VC finance are more developed, and the distance (both physical and cultural) between professional investors and entrepreneurs is smaller, making interactions more productive. All the specifications include year fixed effects.

Three main results emerge. First, the firm-level network effects index is strongly correlated with the use of token-based finance (column 1). Second, controlling for network effects, firms located in one of the VC hubs are less likely to use token-based funding (column 2). Interestingly, the coefficient of the interaction term between *VC Hub* and *Network Index* is not significant, suggesting that even firms with large network effects are less likely to choose ICO when located in a VC hub. Third, entrepreneurial quality appears to be positively associated with ICO funding (column 3), and particularly so when professional investors participate in fund raising (column 4). Moreover, ICOs are more likely to be subscribed by professional investors when firms are located in a VC hub (column 4).

Next, we analyze how consumers engagement at the firm level varies with network effects and funding methods. Table 4 shows coefficient estimates for an OLS regression of (log of) web traffic in 2019 on the *Network Index,* a dummy variable (*ICO Firm*) that takes value 1 if the firm raised capital though an ICO during the observation period, and an interaction term between *Network Index* and *ICO Firm.* Other controls include the total amount of capital raised, the total number of rounds, the variable VC Hub, round-year and founding-year fixed effects. The estimation results show that both *Network Index* and *ICO Firm* are positively correlated with consumers engagement (columns 1 and 2). However, the network effect seems to originate mostly from firms that raised capital through an ICO (column 3). We repeat this exercise with web traffic data from 2021, using a more parsimonious specification due to the substantial drop in the number of observations. Results are qualitatively similar, but the significance of the estimates decreases (Table 5).

To summarize, our empirical analysis shows that

1) The probability of using ICOs to finance new projects increases with network effects (1a) and with entrepreneurial quality (1b), and decreases with the efficiency of local VC markets (1c). The participation of professional investors in ICOs is more common in VC hubs (1d). Moreover,

2) ICO funding appears more effective than VC funding at amplifying network effects and achieve higher levels of consumers engagement.

In what follows we develop a theoretical model that rationalizes these empirical facts.

5 Model

Overview

There are three types of agents: entrepreneurs, professional investors (VCs), and consumers. All agents are risk-neutral. The timeline unravels over two stages, the funding stage ($t = 0$) and the market stage ($t = 1$).

During the funding stage, the penniless entrepreneur seeks funding, which can be obtained through an ICO and/or by raising capital with VC investors. We denote the funding method of choice with $F \in \{ICO; VC; VC - ICO\}$, depending on whether retail, professional or both investors types are allowed to participate in the funding event. With an ICO, the entrepreneur issues tradable utility tokens that can be used in the following period as the only accepted currency to obtain the product or service.[12] ICOs can be open to retail investors (i.e. consumers) only ($F = ICO$) or to both retail and professional investors ($F = VC - ICO$). When provided exclusively by professional VC investors ($F = VC$), funding instead consists of "traditional" capital injections in the form of equity.

The entrepreneur uses funds obtained at $t = 0$ to generate an output (the product) which is released on the markets at $t = 1$. During the market stage, consumers decide whether to become users, based on their valuation of the product. If the project is financed through an ICO, retail investors can become users by converting the tokens acquired in the previous period (at price τ_0). Alternatively, consumers who do not hold tokens at $t = 1$ (i.e. those who did not participate in the ICO) can become users by purchasing tokens on a crypto-exchange (at price τ_1) and subsequently redeeming them against the product. If at $t = 0$ the entrepreneur chooses to receive funding only from professional VCs, consumers become users by purchasing the product (at price p) on a regular product market. In the market stage, each user chooses whether to actively engage with other users (e.g. by frequently posting content on a platform).

The Project. Capital is used to install capacity and start the production of the firm's service or product. We assume a simple production function where capital is the only input and K units of capital invested at $t = 0$ generate $N = f(K)$ units of output at $t = 1$, where $f(K)$ is concave and twice differentiable function. For simplicity we assume $f(K) = \sqrt{K}$. The

[12]See Schilling and Uhlig [2019]

size of the initial investment K is endogenous, and it is chosen by the entrepreneur in order to maximize profits.

The project is characterized by its *intrinsic* quality (ω) and network effects intensity (ε). Intrinsic quality refers to product attributes (such as ease of use, reliability, design, etc.) and depends on entrepreneurial ability. Network effects instead arise when the product is such that customers valuation increases with the number of active users. Both intrinsic quality and the intensity of network effects are common knowledge and affect consumers' valuation of the product.

Consumers. There is an infinite mass of deep pocketed (i.e. with large, but finite, spending capacity) consumers who live through both periods. In the market stage ($t = 1$), consumer j's utility depends on product valuation R_j, and on the endogenous engagement choice $C \in \{0; 1\}$. Specifically, consumer j draws utility from consumption as follows

$$U_j = \begin{cases} \theta_j R_j & if\, C = 1 \\ R_j & if\, C = 0 \end{cases} \tag{1}$$

where θ_j indicates consumer's type.

Product valuation has two components, u_j and v, with

$$R_j = u_j v$$

The private component u_j indicates individual use value for the firm's product. It is independently distributed across consumers and takes value of either zero or one at $t = 1$, when the product becomes available on the market. The component v, instead, is common across all consumers and depends on projects characteristics ω and ε. We provide the exact functional form of v in the next section (Assumption 1).

As indicated in equation 1, the utility gained from consumption also depends on whether the user actively interacts with other consumers. Being active (i.e. $C = 1$) requires effort, and we assume that effort affects utility depending on user's type θ_j. Differently from use value u_j, which is observed immediately when the product reaches the market, consumers learn their type θ_j over one period time. In particular, by investing amount $c_j \geq 0$ in the first period, consumers can observe their type in the following period. We can interpret c_j as the cost of getting informed about the project which is necessary to understand one's own tastes with regards to active engagement.

The table below summarizes consumer's action space and possible utility outcomes across the two periods.

$t=0$	$t=1$		
Pay c_j?	Engagement?	$E(U_j \mid u_j = 1)$	$E(U_j \mid u_j = 0)$
Yes	$C=1$	$\theta_j v$	0
	$C=0$	v	0
No	$C=1$	$E(\theta_j)\,v$	0
	$C=0$	v	0

Funding Methods: VC and ICO. Funding can be provided by professional investors, VCs, who operate in a competitive capital market and can, through value-adding services, improve product quality over and above its intrinsic level.[13]

The alternative funding method consists in raising capital K through an ICO. In an ICO, the entrepreneur sells tokens, i.e. digital claims, to investors. She fixes the token price, τ_0, and the funding target K, and runs the ICO on a first-come-first-served basis, that is tokens are issued and allocated until the total bid amount equals the funding target. If the target is not reached, the ICO fails and the entrepreneur returns the committed funds to the bidders.

Each token bought at $t=0$ gives investors the right to either redeem it against *one* unit of product or to sell it at price τ_1 in the next period. Notice that, since the entrepreneur fixes this token-to-product "conversion ratio" to one, the token price at $t=1$ simply reflects customers' valuations for one unit of output and can be expressed in fiat currency.Tokens are listed and traded on a crypto-exchange where sellers pay fees proportional to token prices, so that the net

[13] In addition to providing financing, VCs provide other services that can substantially improve outcomes of portfolio firms (see, e.g., Berglof [1994]; Casamatta [2003]; Hellmann [1998]; Schmidt [2003]; Ueda [2004]; Chemmanur et al. [2011]). These services are provided through intense interactions between VCs and portfolio companies, and include sharing of customers and investors networks, strategic and operational guidance, human resources management, and product development (Gompers et al. [2020]).

proceed from selling one token is $\tau_1\phi$ (with $0 < \phi < 1$). Differently from VC funding, ICOs can be subscribed by retail investors (i.e. consumers). If both investors types participate in the ICO, the entrepreneur sets two (potentially different) initial token prices, τ_0^{VC} and τ_0^{R}, depending on whether buyers are professional or retail investors. In practice this can be done by holding a pre-sale event where only professional investors can participate, before the actual ICO - open to the general public - takes place.

5.1 Consumers and Funding Methods: Key Assumptions

Consumers

Assumption 1: Valuations with Network Effects. *The common component v in valuation R_j is*

$$v = \begin{cases} z_{F,\omega} A^{\varepsilon} & if\ A \geq 1 \\ z_{F,\omega} & otherwise \end{cases}$$

where A is the number of active users, $\varepsilon \in [0, 1)$ is the intensity of network effects, and $z_{F,\omega}$ is the final product quality.

We can think of $A = 1$ as the normalized "critical mass" of active users above which network effects start generating positive externalities. Additionally, valuation increases with the *final* quality of the product, $z_{F,\omega}$, which is a function of intrinsic quality ω and of the (endogenously determined) funding method F. We provide the exact functional form for $z_{F,\omega}$ with Assumptions 4 and 5 below.

Assumption 2: Quasi-linearity of Consumer's Utility. *For the first n units of product in the consumer's possession, the private component u_j is stocastically distributed as a Bernoulli with $E(u_j) = \alpha$, and its value is realized at $t = 1$. Any unit of product in excess of quantity n has no use value, i.e. $u_j = 0$.*

In other words, consumers' expected utility is quasi-linear in quantities, and the maximum utility generated by consumption is nv. For expositional purposes we set $n = 1$.

Assumption 3: Consumer's Type. $\theta_j \in \{\theta_H; \theta_L\}$, *with* $\theta_H = 1$, $\theta_L < 1$,*and* $Prob(\theta_j = \theta_H) = \gamma$

This implies that, for consumers with type θ_L being active is a pure cost with negative utility, while for those with type θ_H the loss is compensated by utility gains, which we can think as related to personal traits (e.g. altruism, openness, narcissism, etc.) or as deriving from potential benefits of visibility.

Funding Method

Assumption 4: VC investors and product quality. *If a share $\beta > 0$ of total investment K is raised from VCs, the final product quality is*

$$z_{F,\omega} = \omega\left[(1+\beta)\,h\right]$$

where $F \in \{VC; VC - ICO\}$ and $h \in \left[\frac{1}{2}, 1\right]$ is the efficiency of value-adding services and it is common across VCs. In other words, VCs can improve intrinsic quality ω by a factor of $(1+\beta)\,h$. Importantly, final quality is increasing in VC's "skin-in-the-game", as the term β indicates the level of VC's capital commitment in proportion to total investment.[14] It can be argued that VC's incentives to exert effort are generally understood to be proportional to the ratio of capital commitment to total VC wealth (rather than total investment in a specific project, as per Assumption 1). In Appendix A we show that our assumption is consistent with this view when VCs are homogeneous in terms of efficiency of value-adding services but heterogeneous in terms of wealth. In this context, the entrepreneur will optimally match with a VC whose total wealth is as close as possible to the optimal project's scale in order to extract the most benefits from VC's services.

Differently from VCs, retail investors are typically remote from the entrepreneur and do not have the skills to contribute to the project's improvement. Therefore we assume that

Assumtpion 5: Retail investors and product quality. *If funding is obtained by consumers*

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Existing empirical evidence shows that investors with larger stakes (i.e. lead investors) are generally more actively involved in the monitoring of the portfolio company (Bernstein et al. [2016]).

only ($F = ICO$), the final product quality is the same as intrinsic quality, that is

$$z_{ICO,\omega} = \omega$$

In other words, without the involvement of professional investors, the only driver of product quality is entrepreneurial ability. Notice that when funding is fully provided by VC investors ($\beta = 1$) the final product quality is larger than with $F = ICO$ funding, that is $z_{VC,\omega} \geq z_{ICO,\omega}$.

Finally, crucial for our model is the idea that entrepreneurs can reach out to their investors community by sharing their vision, providing updates on the project, releasing information on the product's features, distributing provisional versions of the service. We assume that this flow of information between $t = 0$ and $t = 1$ mitigates consumers' costs of learning their type θ_j. Formally,

Assumption 6: Cost of type-discovery. *The cost of becoming informed on θ_j is $c_j = 0$ if consumer j participates in the funding stage as an investor, and $c_j > 0$ otherwise.*

Since households normally receive information on several different consumption options simultaneously, Assumption 2 is meant to capture the idea that, due to cognitive and temporal limitation on how much information one can process, consumers with multiple alternatives have higher attention costs when it comes to evaluate one specific project as compared to investors for whom information on that project is more salient (Reis [2006], Barber and Odean [2008]). Said differently, consumers who are not investors are more likely to be rationally inattentive than consumers who are investors.

Assumption 1 formalizes our notion of network effects as based on the number of *active* users, while Assumption 3 defines the conditions under which being active can be optimal for individual consumers. Assumption 2 implies that, in an ICO, the only reason for retail investors to buy more than n tokens is the expectation of token price appreciation, as no utility is generated by consumption. The specific comparative advantages of the two funding methods emerge from assumptions 4 to 6 : while ICO funding facilitates consumers activism by reducing the costs associated with type-discovery for potential users, VC funding improves final product quality.

5.2 Optimal Scale and Entrepreneurial Payoffs

The goal of our study is to understand how the relative comparative advantages of traditional VC and token-based finance affect entrepreneurial funding choices. To this end, we first analyze entrepreneur's optimal choice of scale conditional on each of the three funding options (K_F^*) and derive final expected payoffs (denoted with X_F^*). We then compare payoffs under each financing method to determine which of the funding method is ultimately preferred depending on parameters h and ε (see Section 5.3).

In order to solve her optimization problem, the entrepreneur forms expectations on customer's valuation at $t = 1$, which, in presence of network effects, depends on the final number of active users (A). Recall that each user's decision to become active ($C \in \{0, 1\}$) depends on her type (θ_j), and that type is unknown to users at $t = 1$ unless they invest c_j in information acquisition at $t = 0$. Therefore, before proceeding with the entrepreneur's optimization problem, we present the following result on consumers' optimality of acquiring information.

Lemma 1. *If $c_j > 0$ consumers never learn their type θ_j.*

Proof. By Assumption 3, conditional on investing c_j at $t = 0$, at $t = 1$ the optimal action is $C = 1$ if $\theta = \theta_H$ and $C = 0$ otherwise.[15] Therefore, conditional on $u_j = 1$, consumer's expected utility at $t = 0$ is

$$E\left(U_j|u_j = 1\right) = \left[\gamma\theta_H + (1-\gamma)\right] v$$

If instead consumers do not invest c_j, θ_j remains unknown at $t = 1$ and the optimal action is $C = 0$ since $E\left(\theta\right) v < v$. In this case, conditional on $u_j = 1$, consumers receive expected utility

$$E\left(U_j|u_j = 1\right) = Max\left[E\left(\theta_j\right) v; v\right] = v$$

as $E\left(\theta_j\right) < 1$.

By comparing the two expressions for $E\left(U_j|u_j = 1\right)$ above, it is immediate to see that the extra expected utility from investing c_j at $t = 0$ is $\alpha\gamma v\left(\theta_H - 1\right) = 0$, as $\theta_H = 1$.[16] Thus, any cost $c_j > 0$ deters consumers from becoming informed.

[15] We use the simplifying assumption that consumers always break indifference by choosing $C = 1$ to avoid further parameters restrictions. Of course this is unnecessary if we set $\theta_H > 1$.

[16] With $\theta_H > 1$, we can restate this lemma by assuming that c_j is sufficiently large for consumers who do not invest in the project, and that $E\left(\theta_j\right) < 1$. For example, we could assume: $\theta_L = 0$, $\theta_H \in (1, 2)$, $\gamma \leq \frac{1}{2}$, and $c_j = v$ if consumer j does not invest and $c_j = 0$ otherwise, implying that $c_j > \alpha\gamma v\left(\theta_H - 1\right)$ for non investors.

In other words, consumers learn their type in advance only if gathering information on the project involves no extra costs, i.e. if $c_j = 0$. Due to Assumption 6, this only happens when consumers invest in the project by participating in the ICO.

5.2.1 VC Funding (Professional Investors Only)

First, we analyze the simplest case when funding is conducted exclusively with one professional investor, the VC, who contributes capital K in the form of equity, receiving share q^{VC} of total profits. We proceed solving this subgame by backward induction.

Market Stage, $t = 1$.

With an infinite mass of consumers, the entrepreneur maximizes total revenues by setting the product price equal to consumer's maximum willingness to pay. [17] By Assumption 6 and Lemma 1, consumers with $u_j = 1$ choose $C = 0$ as $E(\theta_j)\, v < v$. Thus, their maximum willingness to pay for the product is v and, consequently, the product price is $p = v$.

Since VC's share of invested capital is $\beta = 1$, the final quality is $z_{VC,\omega} = 2\omega h$ (as per Assumption 4). Moreover, since all consumers choose $C = 0$, the number of active users A is equal to zero, which implies $v = z_{VC,\omega}$ (from Assumption 1). Therefore,

$$p = 2\omega h$$

Funding Stage, $t = 0$**.** With competitive VC capital markets, the VC's equity share q^{VC} must be such that investment equals returns, i.e. $K = 2\omega h\sqrt{K}q^{VC}$, implying that the entrepreneur's payoff is maximized by setting

$$K^*_{VC} = (\omega h)^2$$

which implies

$$X^*_{VC} = (\omega h)^2 \tag{2}$$

Unsurprisingly, the final payoff is increasing in entrepreneurial ability and VC efficiency.

5.2.2 ICO with Retail Investors

We now consider ICO funding when capital is raised only with retail investors, i.e. consumers.

[17] With equity funding, since costs have already been paid at $t = 0$, the entrepreneur maximizes her profit by maximizing revenues.

To distinguish between consumers who buy the product in the market at $t = 1$ and consumers who, having bought their tokens at $t = 0$, convert them (becoming users) at $t = 1$ we call the former "late adopters" and the latter "early adopters".

Market Stage, $t = 1$. Similarly to the VC funding case, late adopters (i.e. consumers with $u_j = 1$ who did not participate in the ICO) optimally choose $C = 0$ and their maximum willingness to pay for the product is v. With an infinite mass of late adopters, sellers set token price equal to their maximum willingness to pay, that is

$$\tau_1 = v \tag{3}$$

Proposition 1: Optimal Token Redemption. *All ICO investors with $u_j = 1$ ($u_j = 0$) convert (sell) their tokens.*

This immediately follows from the pricing equation in 3. Each consumer receives $\phi\tau_1$ if she sells her token or v if she converts it. Since $\phi < 1$, we have that $v > \phi v = \phi\tau_1$, or in other words, the trading fee "forces" conversion when $u_j = 1$. On the other hand, when $u_j = 0$ consumers strictly prefer to sell their token and get $\phi\tau_1$ rather than converting it into a product for which they have zero value. Thus, both the entrepreneur and ICO investors with $u_j = 0$ (i.e. zero use value) sell their tokens to late adopters at price τ_1 and receive $\phi\tau_1$.

Additionally, early adopters know their type θ_j (by Assumption 6 and Lemma 1) and become active only if $\theta_j = \theta_H$.

Funding Stage, $t = 0$**.** In the ICO, the entrepreneur issues N tokens and sells share q^{ICO} of the total tokens issued to the public (retaining share $1 - q^{ICO}$ for herself). Her expected payoff X_{ICO} equals the future proceeds from the sale of the tokens left in her possession, that is

$$X_{ICO} = \phi\tau_1 \left[N\left(1 - q^{ICO}\right)\right]$$

Since total number of tokens in circulation must equal total output, we have that $N = \sqrt{K}$. Moreover, the initial investment K must be fully funded through the ICO, implying

$q^{ICO}\sqrt{K}\tau_0 = K$. Thus, entrepreneurial payoff can be rewritten as

$$X_{ICO} = \phi\tau_1\sqrt{K}\left(1 - \frac{\sqrt{K}}{\tau_0}\right) \tag{4}$$

The entrepreneur chooses τ_0 and K in order to maximize X_{ICO}.

Proposition 2: No Excess Speculation. *The entrepreneur serves only the demand of tokens for (possible) consumption by setting the token price τ_0 such that*

$$\tau_0 > \tau_1\phi$$

To see this result, first notice that, anticipating their optimal choices in the next period, consumers' maximum willingness to pay for one token in the ICO is

$$WTP_{n=1} = (1-\alpha)\,\phi\tau_1 + \alpha v$$

whereas for any additional token we have $WTP_{n>1} = \tau_1\phi$, due to Assumption 2. In other words, the rationale for buying tokens in excess of one is pure speculation, i.e. token price appreciation.

Now suppose $\tau_0 \leq \tau_1\phi$. In this case, every investor will bid for the whole ICO, as they can profit from both the conversion of one token and from the sale of the remaining ones. Since bids can be submitted in an anonymous fashion (i.e. investors can send their bids through multiple crypto-wallets), the entrepreneur cannot optimally ration allocations. Thus, in a first-come-first-served ICO, all tokens are allocated to the first bidder. It follows that the ICO is subscribed by one retail investor only, who becomes an active user with probability $\alpha\gamma$. Thus, the expected number of active users is $A = \alpha\gamma < 1$, implying that $v = \omega$. It follows that $\tau_1 = \omega$, and the entrepreneur maximizes equation 4 by setting $\tau_0^* = \phi\tau_1 = \phi\omega$. This results in a final payoff equal to $X_{ICO} = \phi\omega\sqrt{K} - K$, which is clearly dominated by the expected payoff with VC funding (independently of VC efficiency) as $\phi < 2h$. In other words, since network externality effects are strictly positive only when $A > 1$, the entrepreneur is better off shutting down demand for pure speculation by setting $\tau_0 > \tau_1\phi$. Consequently,

Corollary 1: *In an ICO each consumer only bids for $n = 1$ token.*

With $\tau_0 > \tau_1\phi$, and conditional on the ICO being successful, the number of expected active users depends on the number of investors ($\frac{K}{\tau_0}$), on the share of investors with positive use value (α), and on the share of investors with $\theta_j = \theta_H$ (γ). Thus, $A = \alpha\gamma\frac{K}{\tau_0}$ and equation 4 can be written as

$$X_{ICO} = \phi\left[\omega\left(\alpha\gamma\frac{K}{\tau_0}\right)^{\varepsilon}\right]\sqrt{K}\left(1 - \frac{\sqrt{K}}{\tau_0}\right) \tag{5}$$

Since $\tau_1 = v$ (from equation 3), let us write $WTP_{n=1} = \Phi\tau_1$ where $\Phi = (1-\alpha)\,\phi + \alpha$.

Proposition 3: Optimal Token Pricing. *The optimal token price in an ICO is*

$$\tau_o^* = \Phi\tau_1$$

To see this, first notice that $\tau_0 > \Phi\tau_1 = WTP_{n=1}$ results in ICO failure, as no investor is willing to participate. Thus, τ_0 must satisfy

$$\tau_1\phi < \tau_0 \leq \Phi\tau_1 \tag{6}$$

where the lower bound of this range is established in Proposition 2.

Equation 5 is concave in τ_0, but the value of τ_0 that satisfies the first order condition violates the feasibility constraint in range 6 (proof in Appendix B). Therefore, the only finite equilibrium token price equals the upper bound of range 6, namely consumer's maximum willingness to pay for the product.

Importantly, Propositions 1 to 3 reveal that, in the context of our model, the presence of trading fees allows entrepreneurs to price-discriminate speculators from potential users. This is crucial for ICO optimality since only potential users contribute to the generation of network effects.

It is also worth noting that the result in Proposition 3 is conditional on the ICO being fully subscribed. Of course, ICO success depends on investors optimal participation strategy. Since investor's payoff increases with other investors participation (due to network effects), this setting displays the feature of strategic complementarities, where "an increase in one player's strategy increases the optimal strategy of the other player" (Cooper and John [1988], p.442). Differently from other settings, however, strategic complementarities do not result in multiple equilibria, provided that consumers attach a non zero probability to the event of success. This is because, if the fund raising goal K is not achieved (i.e. the ICO fails), investors get their money back, while if the ICO succeeds investors get expected utility equal to the difference between $WTP_{n=1}$ and $\Phi\tau_1$. It is possible for the entrepreneur to make expected utility from participating in the ICO strictly positive by applying a small discount $\delta \in (0,1)$ to τ_o^* such that $\tau_o^*\delta$ belongs to the range in 6. In this case, participating is the optimal strategy for all consumers and the ICO is fully subscribed. For simplicity, we present results for the limiting case where $\delta \to 1$.

Combining the result in Proposition 3 with equation 3 , we have that the optimal token price solves the following fixed point problem

$$\tau_0^* = \Phi\left[\omega\left(\alpha\gamma\frac{K}{\tau_0^*}\right)^{\varepsilon}\right]$$

implying that $\tau_0^* = (\Phi\omega)^{\frac{1}{1+\varepsilon}}(\alpha\gamma K)^{\frac{\varepsilon}{1+\varepsilon}}$.

Importantly, the impact of network effect intensity ε on final equilibrium price τ_0 is ambiguous. This is because as externality effects increase, token prices go up, reflecting higher future valuations (direct effect). However, the number of *distributed* tokens decreases, which results in a lower number of ICO investors. This shrinks the size of the initial customer base, ultimately decreasing late adopters' willingness to pay (indirect effect). The overall impact of these feedback effects on prices (and on profits) depends on the endogenous project scale K. Intuitively, when K is relatively large (small) the direct (indirect) effect dominates.

By replacing τ_0 with τ_0^* in equation 5 and maximizing with respect to K we obtain

$$K_{ICO}^* = \left[\frac{(3\varepsilon+1)}{2(1+\varepsilon)}\right]^{\frac{2(1+\varepsilon)}{1-\varepsilon}}\left[\Phi\omega(\alpha\gamma)^{\varepsilon}\right]^{\frac{2}{1-\varepsilon}} \tag{7}$$

and

$$X_{ICO}^* = (\Phi\omega)^{\frac{2}{1-\varepsilon}}\left\{\phi(\alpha\gamma)^{\frac{2\varepsilon}{1-\varepsilon}}\left[\frac{(3\varepsilon+1)}{2(1+\varepsilon)}\right]^{\frac{2(1+\varepsilon)}{1-\varepsilon}}\left[\frac{1-\varepsilon}{(3\varepsilon+1)}\right]\right\} \tag{8}$$

Proposition 4: Non-Monotonicity of ICO Payoff. X_{ICO}^* *is convex in* ε*, and whether or not it is strictly monotonically increasing in the interval* $[0,1)$ *depends on intrinsic quality* ω *and parameters* α*,* γ*, and* ϕ*.*

More specifically, X^*_{ICO} is decreasing (increasing) in ε for $\omega < \frac{1}{\alpha\gamma\Phi}$ ($\omega > \frac{4}{\alpha\gamma\Phi}$), and it is non-monotonic in ε when $\frac{1}{\alpha\gamma\Phi} < \omega < \frac{4}{\alpha\gamma\Phi}$ (see proof in Appendix C).

In other words, somewhat counter-intuitively, with ICO funding the project's payoff is not always strictly increasing with network effects. This is due to the fact that for smaller values of ω a smaller optimal scale is required, which translates into negative (indirect) effects of network size on token prices. As we shall see later, this implies that ICO may not be the optimal funding method even when the intensity of network effects is large.

5.2.3 ICO with Retail and Professional Investors

Finally, we consider the case when the entrepreneur issues tokens with a private sale to a VC (who contributes a share β of total investment K) and a public sale with retail investors. As in the previous funding methods, the entrepreneur charges investors with their maximum willingness to pay, implying that $\tau_0^{VC} = \phi\tau_1$ and $\tau_0^R = \Phi\tau_1$.[18] Not surprisingly, VCs pay a lower price than retail investors.

The entrepreneur chooses VC's share of capital β and project scale K to maximize

$$X_{VC-ICO} = \phi\tau_1\sqrt{K} - K\left[\beta + \frac{\phi}{\Phi}(1-\beta)\right] \tag{9}$$

A closed form solution for this maximization problem can be obtained in the limit where $\phi = 1$. In this case, the optimal share of VC capital is $\beta^* = \frac{1-\varepsilon}{1+\varepsilon}$ and

$$X^*_{VC-ICO} = (h\omega)^{\frac{2}{1-\varepsilon}} B \tag{10}$$

where B is a function of α, γ, and ε.[19]

5.3 Funding Method Optimality

The entrepreneur chooses a funding method for her project by comparing payoffs X^*_{ICO}, X^*_{VC}, and X^*_{VC-ICO}. We can characterize optimality with two main results.

[18] The optimality of $\tau_0^{VC} = \phi\tau_1$ immediately derives from the fact VCs do not contribute towards the creation of an initial customers' base, and therefore entrepreneurs are better off charging the maximum possible price for capital. The derivation of $\tau_0^R = \Phi\tau_1$ can be obtained following the same procedure as in section 5.2.2.

[19] Specifically, $B = (\alpha\gamma)^{\frac{2\varepsilon}{1-\varepsilon}}\left[g(\beta^*)\frac{(3\varepsilon+1)}{2(1+\varepsilon)}\right]^{\frac{2(1+\varepsilon)}{1-\varepsilon}}\left[\frac{1-\varepsilon}{(3\varepsilon+1)}\right]$ where $g(\beta) \equiv (1+\beta)^{\frac{1}{1+\varepsilon}}(1-\beta)^{\frac{\varepsilon}{1+\varepsilon}}$.

Result 1. *The presence of network effects is necessary but not sufficient condition for $F = ICO$ to emerge as the optimal funding method.*

To see this, notice that when $\varepsilon = 0$ we have that $X^*_{ICO} = \frac{1}{4}\omega^2\phi\Phi < (\omega h)^2 = X^*_{VC}$. Additionally, since X^*_{ICO} is strictly decreasing (increasing) in ε when $\omega < \frac{1}{\alpha\gamma\Phi}$ ($\omega > \frac{4}{\alpha\gamma\Phi}$) (from Proposition 4), it follows that

$$\omega < \frac{1}{\alpha\gamma\Phi} \Rightarrow X^*_{ICO} < X^*_{VC} \forall \varepsilon \in [0, 1).$$

In other words, the extent to which entrepreneurs are exposed to the efficiency-network trade-off depends on entrepreneurial ability. In particular, an increase in network effect intensity has two opposite effects on product valuations. The first (positive) is that, holding constant the number of active users, valuations increase due to the amplification mechanism inherent in network effects. The second (negative) arises because, for any given level of investment, an increase in token prices reduces the number of ICO investors (and potential active users). The negative effect of network externalities on product valuations dominates the positive effect when the total amount of capital raised is small. Owing to the decreasing returns to scale, the optimal scale of the project (and therefore, the optimal amount of capital invested) increases with entrepreneurial ability. As a consequence, when ability is low (i.e. $\omega < \frac{1}{\alpha\gamma\Phi}$) VC dominates ICO funding, regardless of both VC efficiency and project's network effects.

Result 2. *$F = VC - ICO$ is optimal only when both VC efficiency and intrinsic quality are large.*

Specifically, using the closed form solution in equation 10, we obtain that $F = VC - ICO$ is the optimal funding choice (i.e $X^*_{VC-ICO} > X^*_{ICO}$ and $X^*_{VC-ICO} > X^*_{VC}$) if both of the following conditions hold

a) $h > \left(\frac{1+\varepsilon}{2}\right)^{\varepsilon+1}\left(\frac{1}{\varepsilon}\right)^{\varepsilon}$

b) $h > \frac{1}{\omega}\left[B\right]^{\frac{\varepsilon-1}{2\varepsilon}}$

implying that ICOs conducted with both professional and retail investors are optimal for relatively large values of h and ω.

These two analytical results are depicted in Figure 1, where we compare payoffs in 2,8, and 10 for different values of ω and we assess funding method optimality in the h - ε space. Payoffs are computed by setting $\phi = 1$ in order to obtain a closed form solution for the optimization problem in 9, but we replicate Figure 1 when $\phi < 1$ through simulation in Figure 2, obtaining analogous results.

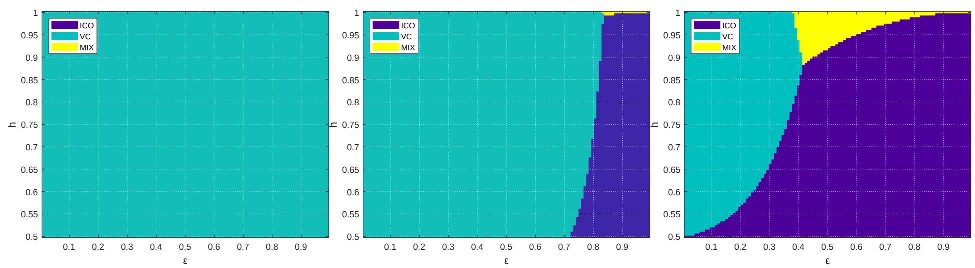
Let us first observe that when ω is low (left panel) the optimal funding method is VC only. As per Result 1, with low levels of intrinsic quality, ICO funding alone cannot generate a sufficiently large customers base to attract late adopters. This implies that, regardless of VC's efficiency, ICO funding adds no value with respect to traditional funding. For intermediate values of ω (middle panel), the initial customers base provided by ICO investors can be large enough to create value for entrepreneurs conditionally on network effects being sufficiently large. However, even when VC funding is least efficient (i.e. when $h = \frac{1}{2}$) it may still be preferred to ICOs for small values of ε. Finally, when ω is large (right panel), the trade-off between ICO and VC funding is meaningful even for small values of ε, and ICO funding with both retail and VC investors emerges as the optimal method as h increases.

The right panel of Figure 1 also shows that the threshold level of network effects beyond which token-based finance represents an improvement over "traditional" finance initially increases as VC effectiveness improves. Said differently, for relatively low values of h, VC and ICO are substitutes, in the sense that higher VC efficiency reduces the relative benefits of exploiting network effects. Interestingly, the relationship between VC and ICO switches to one of complementarity for larger values of h, i.e. in developed VC markets. In particular, ICO funding conducted with both retail and professional investors becomes increasingly more common as efficiency improves (Result 2).[20]

The two main takeaways from our framework are the following. First, network effects are necessary but may not be sufficient to make ICO the optimal funding method, even when "traditional" funding, such as VC, adds no extra value to ventures through advisory and monitoring activities. Rather, consistently with the empirical fact 1b) from Section 4, the optimality of ICO funding depends (positively) on entrepreneurial ability. This is due to the negative feedback loop of externality effects on final product prices which is inherent to the token pricing mechanism. Conditional on the entrepreneurial ability being high, ICO funding is optimal when

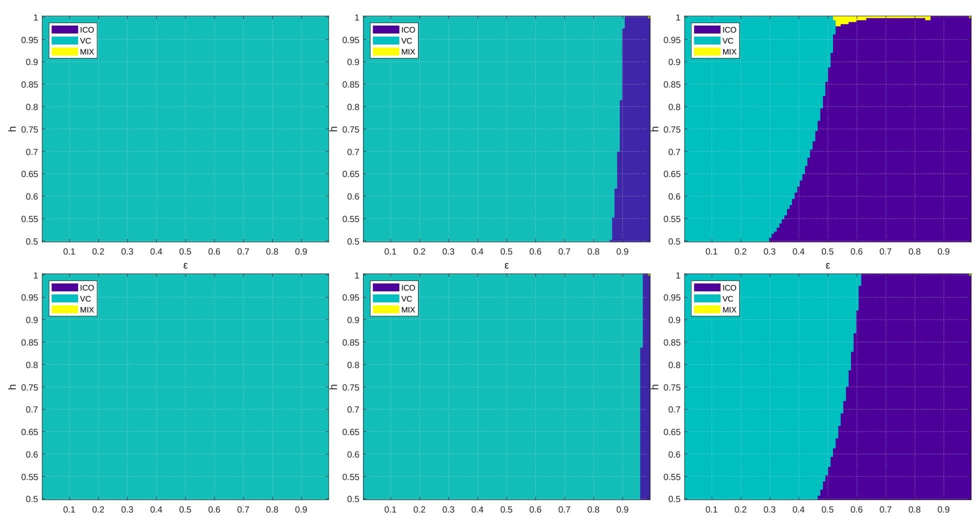
[20] Analytically, this is due to the fact that the threshold level $\frac{1}{\omega}[B]^{\frac{\varepsilon-1}{2\varepsilon}}$ in condition b) is decreasing in ε $\forall\varepsilon \in [0, 1)$.

Figure 1: Funding Method Optimality, $\phi = 1$



This figure presents entrepreneur's optimal funding choices. VC efficiency (h) is on the y-axis and the intensity of network effects (ε) is on the x-axis. Intrinsic quality ω is equal to 2, 6 and 19 in the left, middle and right panel respectively. In all three panels we set $\alpha = 0.5$, $\gamma = 0.5$and $\phi = 1$.

Figure 2: Funding Method Optimality, $\phi < 1$



This figure presents entrepreneur's optimal funding choices. VC efficiency (h) is on the y-axis and the intensity of network effects (ε) is on the x-axis. Intrinsic quality ω is equal to 2, 6 and 19 in the left, middle and right panel respectively. In all three panels we set $\alpha = 0.5$, $\gamma = 0.5$. Parameter ϕ is 0.75 in the upper row and 0.5 in the bottom row.

network effects are large (as per empirical fact 1a) in Section 4).

Second, despite the potential complementarities between professional (VC) and retail (ICO) investors, combining the two funding sources is optimal only when VCs can substantially improve product quality (see empirical fact 1d)). This is because, on the one hand, mixed funding crowds out potential consumers from an investors pool, thus becoming sub-optimal with respect to ICO when network effects are very large. On the other hand, due to lower effort provision, it offers less benefits in terms of value-adding services than VC-only funding.

It is also worth noting that our model's predictions on the empirical relationship between VC efficiency and ICO optimality is not unambiguous. In particular, the optimality of $F = VC - ICO$ versus $F = ICO$ increases with VC efficiency (Result 2). In other words the yellow area in Figure 1 (right panel) expands compared to the blue area as we move south-north along the y axis. This figure, however, also suggests that the optimality of either $VC - ICO$ or ICO (the combined yellow and blue area) is at first contracting and then expanding with h, i.e. the relationship between ICO funding optimality and VC efficiency is non-monotonic. It follows that in an empirical analysis such that in Table 4, columns 2 and 3, where the outcome variable is a dummy that takes value 1 if the funding event is *either* ICO *or* $VC-ICO$, the coefficient on the *VC Hub* dummy can be either positive or negative depending on whether the complementarity or substitutability effect dominates. We interpret the negative sign of this coefficient as evidence that the subsitution effect dominates, which, through the lenses of our model, can be attributed to parameters' distribution (e.g. the distribution of ability ω)

Finally, when parameters α and γ increase ICO is more likely to be the optimal funding method (see Figure 7in Appendix D). Intuitively, this is due to the fact that $\alpha\gamma$ represents the ex-ante probability with which each retail investor becomes an active user. Additionally, the amounts of capital raised predicted by our model match the empirical evidence. In particular, Figure 8 in Appendix D shows that, with randomly and independently distributed values of ω and ε, and for different levels of efficiency, ICO rounds are on average larger than VC rounds.

6 Discussion

In our model, we make two important assumptions regarding entrepreneur's ability to commit to future actions. First, we assume that the entrepreneur can credibly commit to invest capital in production. In principle, however, it is possible for entrepreneurs to divert funds raised in a funding event. While this possibility is arguably remote if funding is conducted with professional investors who are generally able to strictly monitor entrepreneurs, cash diversion is more likely in an environment with poor contract enforcement such as that of unregulated ICOs, where there are virtually no incentives for entrepreneurs to carry on with production. In our model, we can accommodate this consideration by assuming that entrepreneurs can appropriate the funds raised in ICO but need to spend share $1-\lambda$ of capital to abscond from potential legal actions. In this case, cash diversion is preferred to investment when $\lambda K^*_{ICO} > X^*_{ICO}$. Intuitively, when this condition holds and in the absence of a credible commitment device (e.g. reputation concerns, legal contract enforcement), it is not possible for entrepreneurs to raise capital with an ICO, as investors anticipate diversion. This implies that for

$$\lambda > \frac{\phi}{\Phi}\left(\frac{1-\varepsilon}{3\varepsilon+1}\right)$$

funding can only be raised with VCs or with mixed sources (retail and VC investors), since the presence of VCs among investors guarantees effective monitoring.

Second, like in most previous literature on crypto-finance (e.g. Schilling and Uhlig [2019]), we assume that entrepreneurs promise to only accept tokens as means of payment. This promise however is not credible if the total revenues from selling the product in fiat money are larger than payoff X^*_{ICO}. It can be showed that, in the absence of reputational or legal costs, reneging on this promise is always optimal ex-post.[21] Therefore, in our model, ICOs conducted with retail investors arise as the optimal funding choice if and only if entrepreneurs can credibly commit to only accept tokens as a means of payment for the product. Interestingly, these considerations on entrepreneur's ability to commit suggest that regulatory improvements in terms of investors protection can increase the cost of fund misappropriation and enforcement of

[21] If the entrepreneur reneges the minimum final product price is $p = v = \omega$. Therefore, reneging is the optimal strategy if $\omega\sqrt{K^*_{ICO}} > X^*_{ICO}$. This condition holds when $\omega \geq \frac{1}{\Phi\alpha\gamma}$, namely in the region where ICOs can be preferred over VC funding (see Result 1).

contractual obligations, thus increasing trust in the market and restoring the optimality of ICO funding. In the absence of regulatory oversight, many companies try to signal their credibility by employing KYC verification on team members and experts, for whom reputational concerns might be relevant.

Finally, we assume that each token held by investors can be converted in one unit of product and tokens are non divisible, i.e. investors cannot hold fractions of tokens. It could be argued that non-divisibility may not be optimal from the perspective of the entrepreneur. This is because if each investor held a fraction of token $\eta_j < 1$ the final number of active users would be $A = \alpha\gamma\frac{K}{\tau_0\eta_j}$ which is larger than the number of active users with non-divisibility. To the extent that tokens are assumed to be not infinitely divisible, our results hold up to the constant $\underline{\eta_j}$, which represents the minimum token fraction possible. Alternatively, non-divisibility can arise as an optimal entrepreneurial choice (rather than an assumption) if the cost c_j of learning type θ_j is proportional to individual token holdings. In particular we can assume that $c_j = c\,(1-\eta_j)$, which implies that $c_j > 0$ if $\eta_j < 1$ and $c_j = 0$ if $\eta_j = 1$. In this case, it is optimal for the entrepreneur to impose non-divisibility as by doing so she maximizes the probability of investors turning into active users.

7 Conclusions

We propose a model of entrepreneurial finance where firms optimally choose ICO and/or VC funding to raise capital. While VC's active involvement in firm management through monitoring and advising services improves firm's quality, ICOs allow firms to build a large initial active 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. We show that the trade-off between these two comparative advantages is non trivial, owing to the peculiarities of the token pricing mechanism. As a consequence, ICO emerges as the optimal funding method only when entrepreneurial ability is high. When this condition is met, token-based finance is preferred to traditional funding methods when network effects are large. Moreover, despite the potential benefits of using both funding sources, mixed funding is optimal only in highly developed VC markets.

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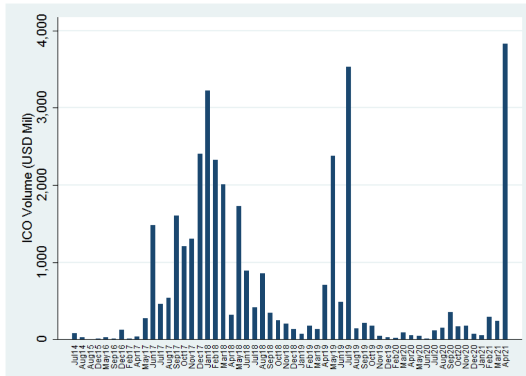
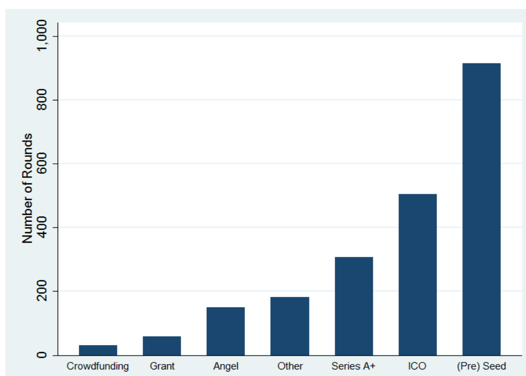
Figure 3: ICO Volumes



Notes: This figure shows ICO volumes in USD Millions. Data are from https://icodrops.com/ for the period 1/1/2014–1/6/2021.

Figure 4



Notes: This figure shows ICO volumes in USD Millions. Data are from https://icodrops.com/ for the period 1/1/2014–1/6/2021.

Table 1: Round

	(1) Amount Mil.	Firm Age (days)	Has Pro Investors	# Pro Investors
ICO	32.89	510.98	0.35	2.60
Series A+	13.17	631.96	0.77	3.45
Other	18.83	494.71	0.69	1.94
(Pre) Seed	1.28	384.99	0.67	2.29
Angel	1.39	322.16	0.55	1.95
Grant	0.67	552.71	0.57	1.09
Crowdfunding	1.73	591.93	0.45	1.07
Total	12.66	460.45	0.60	2.44

Notes: Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Table 2: Firm

	Mean	Median	Min	Max	Obs
Team Size	2.09	2.00	1.00	8.00	1102
Team Media Presence	3.95	0.00	0.00	357.50	1102
Team Experience	1.43	1.00	0.00	9.00	1102
ICO Firm	0.35	.	.	.	1346

Notes: Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Table 3

	(1) ICO=1	(2) ICO=1	(3) ICO=1	(4) ICO with VC=1
Network Index	0.0257**	0.0308**	0.0311**	-0.0173
	(0.0126)	(0.0148)	(0.0133)	(0.0312)
VC Hub		-0.0698***	-0.1001***	0.1958***
		(0.0243)	(0.0201)	(0.0720)
VC Hub X Network		-0.0386		
		(0.0274)		
Team Experience			0.0323***	0.1076***
			(0.0125)	(0.0320)
Firm Age			0.0001***	-0.0001
			(0.0000)	(0.0001)
log(# Founders)			-0.0211	0.0369
			(0.0186)	(0.0488)
Team Media Presence			-0.0003	0.0003
			(0.0003)	(0.0015)
Round-Year FE	Yes	Yes	Yes	Yes
N	2146	2120	1711	366
adj. R^2	0.065	0.069	0.079	0.064

Notes: This table shows coefficient estimates of a linear probability regression model for the choice of funding method. The unit of analysis is the funding round. The outcome variable in columns 1 to 3 is a dummy variable that takes value 1 if the funding type is ICO and zero otherwise. In columns 4 the sample comprises ICOs only, and the outcome is a dummy variable that takes value 1 if the ICO is subscribed by professional investors, and zero otherwise. The independent variables include the *Network Index*. The other controls are firm age, founders team size, founders team experience, founders team media presence, and a binary variable (*VC Hub*) which takes value 1 if the firm is located in the Western US or New England, and zero otherwise. Robust standard errors in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Table 4

	(1) Web Traffic 2019	(2) Web Traffic 2019	(3) Web Traffic 2019
Network Index	0.4198***	0.3712***	0.1568
	(0.1166)	(0.1156)	(0.1721)
ICO Firm		1.0428***	0.8050***
		(0.2253)	(0.2732)
ICO Firm X Network			0.3841*
			(0.2301)
Founding-Year FE	Yes	Yes	Yes
First Round-Year FE	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes
N	947	937	937
adj. R^2	0.245	0.262	0.263

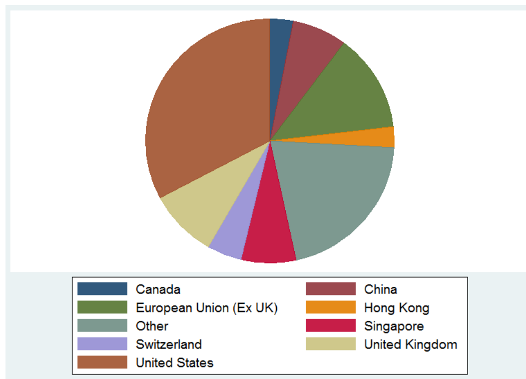
Notes: This table shows coefficient estimates for an OLS regression of (log of) web traffic in 2019 on the *Network Index*, a dummy variable (*ICO Firm*) that takes value 1 if the firm raised capital though an ICO during the observation period, and an interaction term between *Network Index* and *ICO Firm*. Other controls include the total amount of capital raised, the total number of rounds, and the variable *VC Hub*. Robust standard errors in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

Table 5

	(1) Web Traffic 2021	(2) Web Traffic 2021	(3) Web Traffic 2021
Network Index	0.2879*	0.2830*	0.0820
	(0.1682)	(0.1692)	(0.1923)
ICO Firm		0.5614**	0.1988
		(0.2545)	(0.3233)
VC Hub		0.5309*	0.4341
		(0.2966)	(0.3597)
ICO Firm X Network			0.5523$^+$
			(0.3770)
VC Hub X Network			0.1142
			(0.4738)
First Round-Year FE	Yes	Yes	Yes
N	454	447	447
adj. R^2	-0.000	0.011	0.012

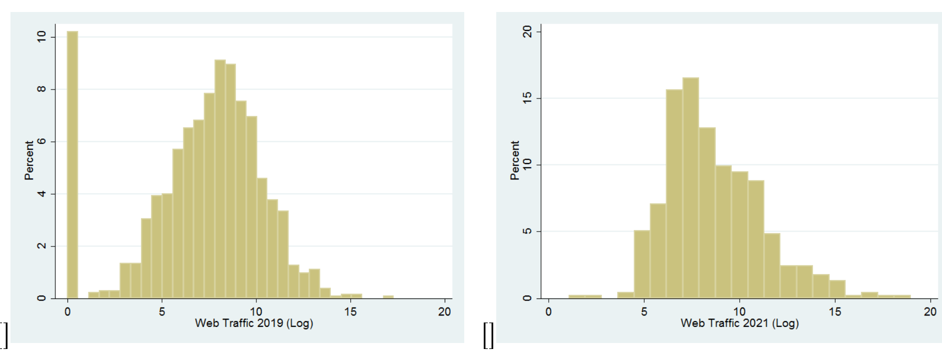
Notes: This table shows coefficient estimates for an OLS regression of (log of) web traffic in 2021 on the *Network Index*, a dummy variable (*ICO Firm*) that takes value 1 if the firm raised capital though an ICO during the observation period, and an interaction term between *Network Index* and *ICO Firm*. Robust standard errors in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Data are from https://www.crunchbase.com for the period 1/1/2015–11/21/2021.

Figure 5: Firm Location



Notes: The table provides the geographical location of firms in our sample across the world. The category "Other" aggregates all countries that have thirty issuers or less . Data are from https://icodrops.com/ for the period 1/1/2014–1/6/2021.

Figure 6: Web Traffic

[] 

Notes: This figure presents the histograms of the log of Web Traffic(average number of monthly visits) measured as of June 2019 (left panel) and November 2021 (right panel). Data are from https://www.crunchbase.com for the period 1/1/2015–1/6/2019.

A VC's Skin-in-the-game (Assumption 4)

Suppose that VCs, each indexed by i, are heterogeneous in the size of their portfolios $P_i > 0$, which is observable at $t = 0$, and that VC capital market is competitive. We can rewrite Assumption 1 as follows

Assumption 1-bis: VC investors and product quality. *If a share $\beta > 0$ of total investment K is raised from VCs, the final product quality is*

$$z_{VC,\omega} = \omega \left[\left(1 + \beta \frac{K}{P_i} \right) h \right]$$

where term $\beta \frac{K}{P_i}$ indicates the level of VC's capital commitment in proportion to the investor's total wealth.

Following the derivation in Section 5.2.1, the entrepreneur's payoff is

$$X_{VC} = \omega \left[\left(1 + \frac{K}{P_i} \right) h \right] \sqrt{K} - K$$

The entrepreneur maximizes X_{VC} by choosing the identity of the VC (namely its portfolio size P_i) and investment size K, subject to $P_i \geq K$. It is immediately clear that the optimal choice of portfolio size requires $P_i = K$, as X_{VC} is decreasing in P_i. By doing so the entrepreneur maximizes VC's contribution towards final product quality.[22]

[22] One may argue that by having $K = P_i$ VC i is not a rational choice for the VC as it would be under-diversified. However, in this setting, where there is no uncertainty and agents are risk neutral, diversification is irrelevant. Moreover, lack of diversification in VC portfolios is in line with empirical evidence. For example, Metrick and Yasuda [2010] show that a median VC fund consists of 12 professionals, of which 5 are partners and makes only 24 investments. Buyout firms, which tends to make larger investments and, hence, require more involvement in each investment, make only 2.4 investment per partner. To allow for a degree of diversification, we could assume that the entrepreneur can split the capital contribution among m VCs where each VC invests $\frac{\beta}{m}K$. The entrepreneur can maximize VCs' contribution towards final quality by choosing m such that $\sum_{i=1}^{m} P_i = \frac{m}{K}$.

B Optimal Token Pricing

Equation 5 is concave in τ_0 and reaches its maximum in $\tau_0 = \sqrt{K}\frac{\varepsilon+1}{\varepsilon} = \tau_0'$. The condition $\tau_0^{'} < \Phi\tau_1$ requires

$$\sqrt{K}\frac{\varepsilon+1}{\varepsilon} < \Phi\left[\omega\left(\alpha\gamma\sqrt{K}\frac{\varepsilon}{\varepsilon+1}\right)^{\varepsilon}\right]$$

which, rearranging terms, implies

$$K^{\frac{1-\varepsilon}{2}} < \Phi\omega\left(\alpha\gamma\right)^{\varepsilon}\left(\frac{\varepsilon}{\varepsilon+1}\right)^{\varepsilon+1} \tag{11}$$

Now suppose the condition 11 above holds. By replacing $\tau_0^{'}$ in equation 5 we obtain

$$X_{ICO} = \frac{1}{\varepsilon+1}\phi\omega\left(\alpha\gamma\frac{\varepsilon+1}{\varepsilon}\right)^{\varepsilon}K^{\frac{\varepsilon+1}{2}} \tag{12}$$

Entrepreneurial payoff is now monotonically increasing in K, implying that, with no upper bound for K, we have $K^* = \infty$. This clearly violates condition 11, implying that $\tau_0^{'} < \Phi\tau_1$ is not a solution to this maximization problem.

Similarly, if we assumed that K is bounded from above, i.e. $K < \bar{K}$, the solution to the maximization of 12 is $K^* = \bar{K}$ and condition 11 does not hold for sufficiently large values of $\bar{K}$.

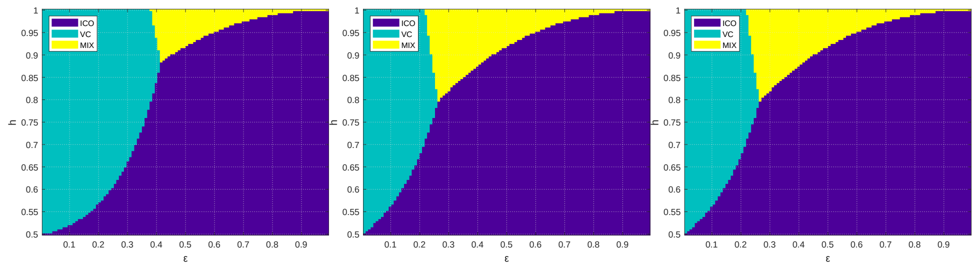
C Non-monotonicity of X^*_{ICO}

Notice that $X^*_{ICO} > 0\ \forall\varepsilon \in [0,1)$ and consider the first derivative of $log\left(X^*_{ICO}\right)$ with respect to ε

$$\frac{\partial log(X^*_{ICO})}{\partial\varepsilon} = \frac{2}{(1-\varepsilon)^2}\left[log\left(\omega\alpha\gamma\Phi\right) + 2log\left(\frac{(3\varepsilon+1)}{2\left(1+\varepsilon\right)}\right)\right]$$

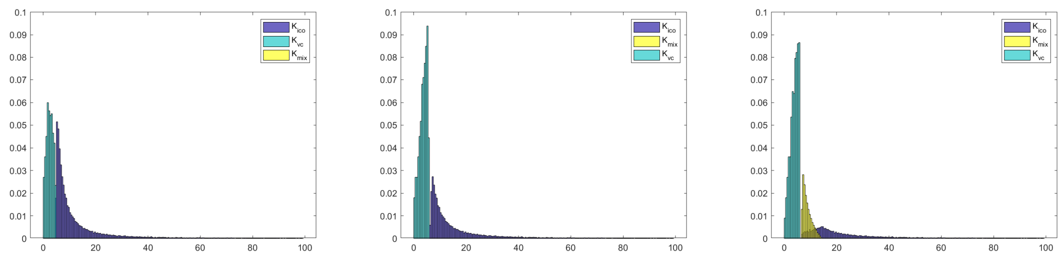
The expression above is negative when $\omega < \frac{1}{\alpha\gamma\Phi}$and positive when $\omega > \frac{4}{\alpha\gamma\Phi}$. It follows that X^*_{ICO} is decreasing (increasing) in ε for $\omega < \frac{1}{\alpha\gamma\Phi}$ ($\omega > \frac{4}{\alpha\gamma\Phi}$), and it is non-monotonic in ε when $\frac{1}{\alpha\gamma\Phi} < \omega < \frac{4}{\alpha\gamma\Phi}$.

Figure 7: Funding Optimality and Parameters α and γ



This figure presents entrepreneur's optimal funding choices. VC efficiency (h) is on the y-axis and the intensity of network effects (ε) is on the x-axis. The left panel captures the baseline case of $\omega = 19$, $\alpha = 0.5$,$\gamma = 0.5$ and $\phi = 1$. In the middle panel, we increase the value of α to 1, but keep all other parameters at the baseline values. In the right panel, we increase the value of γ to 1.

Figure 8: Capital Distribution as a function of h



This figure presents the capital distribution choices in the space of enterpreneiral productivity ω and the strenght of network effects ε for three different values of venture capitalist efficiency h. The left panel corresponds to the lower efficiency 0.55; the middle panel corresponds to moderate efficiency 0.87 and the right panel corresponds to the high effiecncy level 0.98. All other parameters, which are comon across panels, are $\phi = 1$, $\alpha = 0.5$,$\gamma = 0.5$. We assume that ω and ε are uniformly and independently distributed with the support for ω being $[1, 20]$ and the support for ε being $[0, 0.99]$.

D Funding Optimality as a Function of $\alpha\gamma$, and Raised Capital Distributions