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RESEARCH ARTICLE

Decentralized finance (DeFi) markets for startups: search frictions, intermediation, and the efficiency of the ICO market

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Abstract This paper examines the efficiency of the Initial Coin Offering (ICO) market through a search-theoretical lens. *Search* intensity associated with the process of identifying valuable startups is increasing in market granularity. DLT increases market granularity because asset tokenization lowers entry barriers. Lower-end entrants, however, increase aggregate search intensity but may lack search skills. The resulting search-related inefficiency creates a niche for intermediaries or institutional investors that specialize on search. Consistent with the theory, specialized crypto funds increase ICO market efficiency by reducing search frictions, inter alia, by shortening the time-to-funding and increasing the funding amount. At the same time, crypto funds extract sizable economic rents for their intermediation services. Overall, the study relates to the general trade-off between centralization and decentralization in entrepreneurial finance. It suggests that market frictions specific to early-stage crowdfunding of entrepreneurship may prevent "perfectly" Decentralized Finance (DeFi) markets from functioning efficiently.

Plain English Summary Decentralized Finance (DeFi) markets may require a substantial degree of centralization to function efficiently. We show that centralization in the form of institutional investors that intermediate Initial Coin Offerings (ICOs) lead to, first, shorter time periods to reach fundraising goals and, second, higher valuations. In a search-theoretical model, we quantify the extent to which centralization mitigates frictions in a decentralized market. Centralization reduces trading delays and improves decentralized market efficiency especially in times of market downturns and when there is uncertainty about the team or product quality. Thus, the principal implication of our study is that decentralized markets for startups may not be optimal for society. Centralization is valuable because it improves the speed with which entrepreneurs and investors meet, and because it mitigates market frictions arising from asymmetric information.

Keywords Entrepreneurial finance · Blockchain-based crowdfunding · Initial Coin Offering (ICO) · Tokenization · Crypto funds · Decentralized Finance (DeFi)

JEL Classification G23 · G24 · L26

1 Introduction

New technologies are continuously changing the nature of entrepreneurial finance. The trend goes toward a decreasing degree of intermediation. The rationale is, inter alia, that disintermediation increases the economic transaction surplus that entrepreneurs and investors get to enjoy. For example, equity-based

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crowdfunding and its related forms (for reviews, see Moritz and Block, 2016; Mochkabadi and Volkmann, 2020; Block et al., 2021) have partially eliminated Venture Capitalists (VCs) from more traditional venture financing, which has substantially increased the potential return on investment that investors receive,[1] and it has also expanded the supply-side market for venture financing to previously underserved individual investors. The crowdfunding revolution continues to have a dramatic impact on how ventures raise financing, and it also challenges classic scholarly paradigms in the entrepreneurial finance literature, which resulted in some of the most impactful research in economics and management of the last decade (e.g., Ahlers et al., 2015; Belleflamme et al., 2014; Mollick, 2014).

Decentralized Finance (DeFi) markets for startups are the next stage in the evolution of entrepreneurial finance (Bellavitis et al., 2021; Block et al., 2021; Chen & Bellavitis, 2020; Kher et al., 2021). DeFi markets for startups refer to Distributed Ledger Technology-(DLT-)based crowdfunding (more commonly known as token offerings or Initial Coin Offerings, ICOs, see Fisch (2019), for seminal work), which further economize on intermediation costs by replacing crowdfunding platforms, such as *Kickstarter*, with smart contracts (Adhami et al., 2018; Bellavitis et al., 2020, 2021; Benedetti & Kostovetsky, 2021; Boreiko & Risteski, 2021; Campino et al., 2022; Chalmers et al., 2022; Fisch, 2019; Fisch et al., 2021; Howell et al., 2020; Momtaz, 2020a, 2021c). Therefore, we follow Schueffel (2021) in defining DeFi as a paradigm of peer-to-peer financial service provision without a centralized intermediary. Smart contracts are computer protocols that automate the exchange of investors' financial contributions to ICOs and tokens that often represent claims on ventures' future assets at a predefined exchange rate. The only fee incurring in the execution of a smart contract is the fee to operate the blockchain network. For example, the average transaction cost on the most popular blockchain, *Ethereum*, was less than $2 during January 2022, which reduces transaction costs for crowdfunding to a minimum.[2]

This paper argues both theoretically and empirically that, despite its transactional efficiency, the ICO market is relatively inefficient with respect to "search." Search broadly refers to the process of finding a matching transaction counterparty. The intuition is straightforward: DeFi markets for startups are very granular; that is, they have high levels of *market participation* (anyone with internet connectivity may participate) and *market completeness* (everything can be tokenized). Smart contracts enable that anyone can trade anything with anybody at almost no cost (transactional efficiency). The flip side is, however, that market granularity is proportionate to the required search effort (see, for a recent survey among individual investors, Ante et al., 2022). More individual agents and traded products and services mean that agents wishing to transact have to screen deeper markets, which takes more time, in order to avoid resource misallocations through suboptimal transactions (search-related inefficiency). The problem is plausibly particularly pronounced in the ICO market because DLT and smart contracts promote market granularity and market segmentation (Benedetti & Nikbakht, 2021), while they do not offer a technological solution to facilitate search. For this reason, critics showcase the ICO market to argue that perfectly decentralized fundraising is utopian given the pervasive search frictions, and that entrepreneurial finance may revert back to intermediated markets (e.g., Zetzsche et al., 2020).

Consequently, this paper aims to advance the literature on search in entrepreneurial finance by addressing the following, overarching research question:

How efficient is the ICO market and do search frictions reduce aggregate market efficiency?

The question is important because the current state of the literature on ICOs is ripe with efficiency losses due to market design problems (e.g., Bellavitis et al., 2021; Hornuf et al., 2021; Momtaz, 2021c), but fails in large part to provide an explanation for why novel, specialized intermediaries, so-called "crypto funds," are rapidly entering the ICO market (Fisch & Momtaz, 2020). Crypto funds are a blend of venture-style hedge funds that pool retail investors' funds and channel them through sophisticated trading strategies to tokenized startups in liquid secondary markets for tokens. Crypto funds plausibly have emerged as a response to search frictions in markets for tokens, which are very pronounced due to the high levels of asymmetric information in ICOs (Block et al., 2021; Boreiko & Vidusso, 2019; Zetzsche et al., 2020). This resonates with an

[1] VCs typically charge performance fees of 20% and annual management fees between 1 and 2%.

[2] In comparison, equity-based crowdfunding platforms typically charge fees around 7%.

established literature that intermediaries extract rents from reducing search frictions in decentralized markets (Demsetz, 1968; Rubinstein & Wolinsky, 1987).

Of course, search-related arguments are implicit in many existing works in entrepreneurial finance, and not an innovation of this study. However, to our best knowledge, search has never been explicitly modeled in extant theory nor tested empirically in the context of entrepreneurial finance, which is the principal contribution we claim for this study. For instance, a vast literature examines signaling (for a review, see Colombo, 2021), e.g., in IPOs (Arthurs et al., 2009; Colombo et al., 2019), crowdfunding (Ahlers et al., 2015; Vismara, 2018b, 2016), and ICOs (An et al., 2019; Belitski & Boreiko, 2021; Bellavitis et al., 2020; Fisch, 2019; Giudici & Adhami, 2019; Lee et al., 2022), as well as adjacent arguments, such as information cascades (e.g., Vismara, 2018a). While all these studies implicitly assume search frictions to be an important reason as to why signaling is the prime determinant of success in the competition for entrepreneurial finance, they never make search frictions explicit; in fact, none of these studies mentions "search" at all. Another example is the literature on institutional investments in startups, with a focus on venture capital (Bertoni et al., 2011; Colombo et al., 2010) and ICOs (Fisch & Momtaz, 2020). These studies test whether there is a selection effect in the form that institutional investors are able to pick startups with more favorable growth prospects than non-institutional investors. Again, at the root of the selection effect is search (i.e., institutional investors possess better skills and more resources to screen the market and negotiate deals), albeit the precise nature of search in these markets is never made explicit.

Our eclectic theory draws upon multidisciplinary search theory in decentralized markets, financial intermediation, as well as asymmetric information and limits to signaling literatures in entrepreneurship to propose two overarching hypotheses. The first hypothesis, the ***Decentralized Inefficiency Hypothesis*** (***DIH***), posits that search-related frictions render the ICO market relatively inefficient. Specifically, excessive search in the ICO market reduces the market's aggregate efficiency in at least three distinct ways. First, search frictions imply that the ICO market involves two-sided matching: Startups conduct ICO campaigns to attract investors and investors, in turn, screen the market to identify attractive startups for investment purposes. The time to conduct ICO campaigns often takes several months (Momtaz, 2020a), which is time in which startup-investor matches are delayed. Thus, the first way in which search frictions impede ICO market efficiency is through a delay in token allocations. Second, search is costly. It is costly for startups to market ICO campaigns to investors, and it is costly for investors (in terms of both time and financial resources) to perform a due diligence on potentially interesting investment targets. These search-related costs imply that some investments that would be socially optimal in a frictionless economy do not take place if search costs exceed the anticipated transaction surplus. Therefore, the second way in which search frictions impede market efficiency is in terms of an aggregate underinvestment in high-quality, tokenized startups. Third, because the ICO market is characterized by high levels of asymmetric information and there are limits to signaling, there is substantial uncertainty in the ICO market, which can cause a misallocation of financial resources to undeserving tokenized startups. One way for this to occur is through adverse selection (Hornuf et al., 2021) or moral hazard (Momtaz, 2021c). Thus, the efficiency of the ICO market is also impeded by overinvestments in low-quality, tokenized startups.

The second hypothesis, the ***Intermediated Efficiency Hypothesis*** (***IEH***), posits that new DeFi intermediaries, in particular crypto funds, increase ICO market efficiency by reducing search-related frictions. Intermediaries have long been known for extracting rents by reducing search frictions in decentralized markets (Demsetz, 1968; Rubinstein & Wolinsky, 1987; Schueffel, 2021). Crypto funds develop a competitive advantage in search through economies of scale in crypto-specific human capital investments. Crypto funds screen the market and invest in the best startups, signaling startup quality to the market and certifying project legitimacy (Fisch & Momtaz, 2020). They also reduce search frictions related to post-ICO information production. Given the salient manifestations of moral hazard in the ICO market (Hornuf et al., 2021; Momtaz, 2021c), investors need to monitor startups post-funding and coordinate collective actions against shirking teams, which is problematic for individual investors because they may not be able to detect manifestations of moral hazard or coordinate collective actions directed against such behavior. Crypto funds not only have the skills and resources to search for indicators of startup teams' effort provisions, the threat of exit in liquid secondary markets for tokens may prevent shirking and other forms of detrimental behavior in the first place.

Testing the ***DIH*** and ***IEH*** is challenging. The key difficulty is that both hypotheses are related to ICO market efficiency, which is a relative construct, and a perfectly efficient market is a counterfactual benchmark that is not observed in reality. For this reason, our empirical approach is twofold. The first empirical part involves reduced-form regression analyses of two testable relations that are related to our overall argumentation that the ICO market has pronounced search frictions, which intermediation via crypto funds help reduce. Specifically, we test (i) whether intermediated ICOs are more efficient in terms of the time it takes to achieve the crowdfunding goal, and (ii) whether entrepreneurs in non-intermediated ICOs need to sell their tokens at a discount to attract enough investors.

The two empirical relations are not free of endogeneity concerns. For example, it is possible that only ICOs with strong success prospects are able to secure intermediation services (selection effect), rather than it is the intermediation that shortens the time-to-funding or increases the token value (treatment effect). To this end, we employ several two-stage and instrumental variable approaches to disentangle the true effects of ICO intermediation. The results suggest that (i) intermediated ICOs achieve the crowdfunding goal 25% faster and (ii) non-intermediated ICOs have to offer tokens at a substantial discount of 57%. These results are in line with anecdotal evidence, in particular that non-intermediated ICOs offer tokens at discounts in the range of 50 to 70%. Therefore, these results jointly suggest that ICO intermediation makes the market more efficient in terms of time-to-funding, while ICO intermediaries plausibly are able to extract substantial rents for their services.

In the second empirical part, given the challenging nature of the ***DIH*** and ***IEH***, we juxtapose the reduced-form regression-based evidence with structural estimates from a simple model of the ICO market. The model allows to estimate the market's aggregate efficiency, which is a novelty in the entrepreneurial finance literature. In the model, there are individual investors and intermediaries. Only individual investors enjoy a utility from holding tokens (because the token ownership enables them, for instance, to partake in an online gaming community), while intermediaries have no utility from holding tokens, but they extract rents from trading tokens. Startup firms are heterogeneous in the model with respect to their underlying platform sizes. Intuitively, tokens of large platforms are more valuable than tokens of smaller platforms. We calibrate the model with actual ICO market data covering the 2017–20 period. The model predicts several aggregate quantities very well. Consistent with our reduced-form estimates and findings in related studies (e.g., Bellavitis et al., 2021; Fisch and Momtaz, 2020), the structural estimation of the model shows that intermediaries help reduce trading delays and that search costs are pronounced in the ICO market. Importantly, individual sellers and buyers share the transaction surplus more equally in non-intermediated ICOs than in intermediated ICOs, in which intermediaries pocket the transaction surplus almost exclusively.

Overall, the model-implied estimates suggest that the ICO market creates onlye one-third to one-fifth of the welfare it could potentially create if it were perfectly efficient, with the loss stemming from search-related inefficiency.

Theoretical contributions, practical implications, limitations and avenues for future research are discussed in Sect. 8. Preceding that, we provide some institutional background on DeFi, ICOs, and crypto funds in Sect. 2, derive overarching hypotheses in Sect. 3, discuss data and regression results in Sects. 4 and 5, the formal model in Sect. 6, and the structural estimation in Sect. 7.

2 Institutional background: DeFi, ICOs, and crypto funds

2.1 Decentralized finance (DeFi) and the pursuit of disintermediation

DeFi markets may have several advantages over traditional finance markets. First, DeFi may improve market participation. More individuals and small enterprises may gain (equitable) access to finance because DeFi reduces the entry frictions, such as, for example, through a mitigation of local bias in venture financing (Sorenson et al., 2016) or lending (Becker, 2007). Second, DeFi may make markets more complete by facilitating financial innovations. This could be spurred by the open-source character of DeFi, paired with its lack of borders and focus on interoperability standards (Harvey et al., 2021). Third, DeFi promises a significant reduction in transaction costs stemming from multiple sources (Gao & Li, 2021). For example, disintermediation increases the share of the transaction surplus from which transaction parties can exclusively benefit, the transparency of public ledgers significantly reduces auditing costs, and the deterministic and trustless character of smart contracts minimizes the execution risk.

At the same time, DeFi has yet to address a number of novel and idiosyncratic risks that fall broadly into two categories: intra-protocol and inter-protocol risks. Intra-protocol risks include consensus failures, such as 51% attacks on Proof-of-Work (PoW) blockchains and validator cartels on Proof-of-Stake (PoS) blockchains, as well as intra-protocol arbitrage on automated market maker (AMM) exchanges, known as miner extracted value (MEV) (Daian et al., 2020). Inter-protocol risks include so-called oracle attacks, in which biased or fake outside information is fed into smart contracts, and "flash loans" that pave the way for inter-contract arbitrage (Wang et al., 2021).[3] Both intra- and inter-protocol risks have a common attribute in that they represent technical vulnerabilities that are extremely difficult for individual platform users to detect or even understand. Therefore, these risks distinguish DeFi from intermediated financial markets. The consequences of these risks may be salient in crowdfunding markets, such as the ICO market, because individual backers may not possess the technological knowledge to adequately evaluate the novel protocol risks.

2.2 The DeFi market for startups: initial coin offerings (ICOs)

Token offerings (or initial coin offerings, ICOs) are an entrepreneurial finance mechanism that shares some common features with crowdfunding, venture capital, and initial public offerings (for an excellent recent review, see Brochado and Troilo, 2021). Specifically, ICOs have evolved from crowdfunding by employing DLT to both issue and exchange stakes in startup firms (Bellavitis et al., 2021; Fisch, 2019; Howell et al., 2020; Momtaz, 2020a). ICOs are peer-to-peer startup financing transactions that rely on smart contracts to automate trustless transactions between entrepreneurs and investors (Fisch et al., 2022; Rawhouser et al., 2023). In an ICO, an entrepreneur raises venture financing by selling cryptographically protected digital assets, known as tokens or coins, to investors. Tokens can represent different types of value and rights. Cryptocurrency tokens are mere mediums of exchange, such as Bitcoin; security tokens may include voting and control rights; and utility tokens are payment instruments (Howell et al., 2020; Lambert et al., 2021). Utility tokens are the most frequently issued token type in ICOs (Bellavitis et al., 2020), though developments in ICO regulation have initiated a gradual shift to security token offerings (Lambert et al., 2021). Utility tokens are voucher-like assets that can be redeemed for one unit of the venture's future product or service. The reliance on DLT means that ICO investors require not only business skills but also a great deal of technological knowledge (Bellavitis et al., 2021; Fisch, 2019). Unlike other entrepreneurial financing mechanisms, ICOs integrate the full spectrum of "ticket sizes", ranging from micro-cap ICOs (<\$100,000) to mega-cap ICOs (>\$1,000,000, such as the *EOS* campaign, with more than \$4 billion raised).

The first ICO (*MasterCoin*) took place in July 2013, and the market has steadily evolved since then. Figure 1 shows the evolution of the market for token offerings over the 2017–2020 period. During that time, roughly 5,500 token offerings were completed, with the majority in 2018.

Bellavitis et al. (2021) estimate that 2,598 token offerings raised an aggregate funding amount of \$12.3 billion in 2018 alone.

Utility token offerings are often thought to be perfectly disintermediated peer-to-peer transactions and issued tokens are typically traded post-ICO in liquid secondary markets. Smart contracts allow entrepreneurs and investors to automate the transaction in a trustless way, thereby redistributing the transaction surplus exclusively to entrepreneurs and investors; in contrast, intermediaries in crowdfunding or initial public offerings typically charge a fee of 5–7%. Disintermediation might also democratize entrepreneurial finance markets by lowering both supply- and demand-side entry barriers (Butticé & Vismara, 2022; Fisch et al., 2022; Meoli et al., 2022; Rawhouser et al., 2023), leading to more complete markets with higher participation. Moreover, because tokens can be traded at close-to-zero transaction costs and limited trading delays through DLT, ICO aftermarkets are highly liquid. Liquid post-ICO token exchange markets reduce startup firm discounts associated with illiquidity (Barg et al.,

[3] See Carter and Jeng (2021) for an overview of DeFi protocol risks.

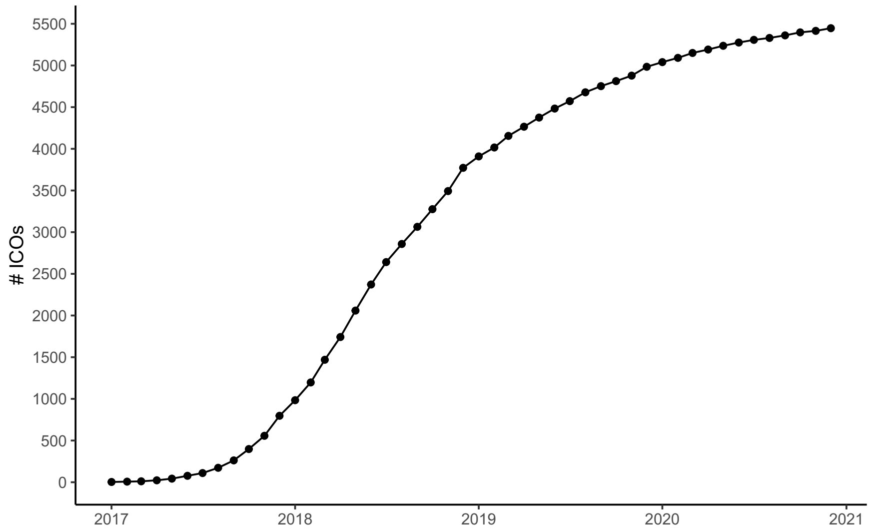

Fig. 1 Evolution of the ICO market

2021) and provide investors with rapid exit opportunities (Fisch & Momtaz, 2020; Momtaz, 2020a). Facilitated trades of stakes in startups might make entrepreneurial finance markets more efficient (e.g., by means of (fair) token valuations obtained from equilibrium prices in liquid token exchange markets that are informative for the market; see Momtaz, 2021c), thereby improving capital allocation to the best entrepreneurial projects and potentially promoting long-term economic growth (Acs & Szerb, 2007; Audretsch, 2018; Bellavitis et al., 2020).

Empirical works are mostly concerned with success determinants of token offerings (e.g., Adhami et al., 2018; Belitski and Boreiko, 2021; Bellavitis et al., 2020; Bellavitis et al., 2021; Fisch, 2019; Giudici and Adhami, 2019; Hornuf et al., 2021; Howell et al., 2020; Momtaz, 2020a). The roles of search, intermediation, and aggregate token market efficiency represent a void in the literature.

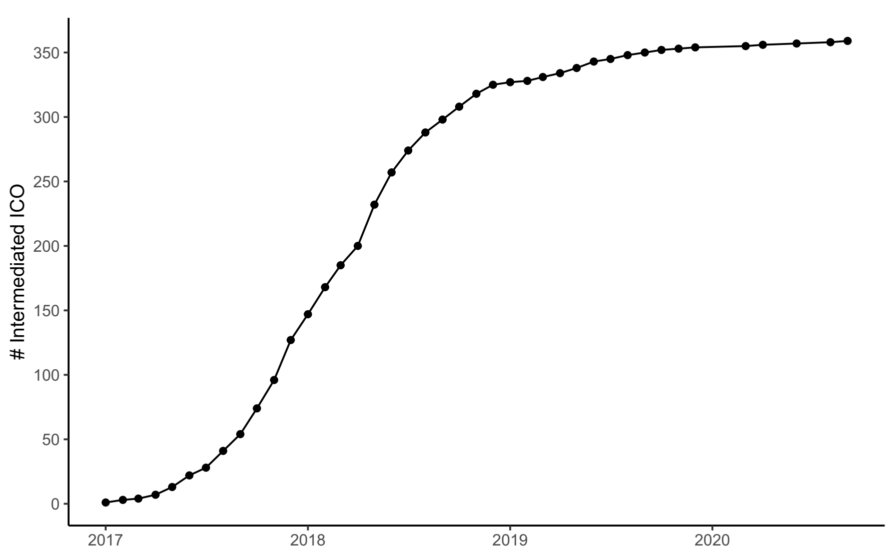

Fig. 2 Evolution of intermediation in the ICO market

2.3 New intermediaries entering the ICO market: crypto funds

Structural problems in the ICO market, such as the systematic manifestation of moral hazard (Hornuf et al., 2021; Momtaz, 2021c) and regulatory (Cumming et al., 2019) and informational frictions (Bourveau et al., 2022), have led to the emergence of a novel, specialized intermediary: the "crypto fund." Most crypto funds resemble venture capital or hedge funds, with the important difference that they trade in "non-securities." The number of crypto funds is rapidly growing. More than 800 crypto funds are active and have aggregate assets under management to the amount of \$57 billion in the first quarter of 2021. The average crypto funds gross return in the first quarter of 2021 was 98%, slightly below Bitcoin's 103%. Like most hedge funds, a large portion of crypto funds are domiciled in the British Virgin Islands or Cayman Islands for tax, legal, or other regulatory reasons, although half of them hold primary offices in the U.S.[4] Figure 2 illustrates the penetration of the market for token offerings by crypto funds over the 2017–2020 period.

Crypto funds are an intriguing asset class because they differ from traditional venture capital funds in several important ways. First, crypto funds mostly trade in non-securities, avoiding much of the regulation traditional funds face. Trading in non-securities largely exempts them from the *Investment Company Act*, which enables them to cater to a new market of small and individual investors, who are not *accredited* or *qualified* in the legal sense (Mokhtarian & Lindgren, 2018). Indeed, crypto funds attract small investors with significantly lower minimum investment requirements. According to Crypto Fund Research (2021), the median minimum fund investment amounts to \$100,000. Moreover, crypto funds are largely exempted from the *Advisers Act*. This lifts limits on performance fees that can be charged to small investors, making crypto funds more financially attractive (albeit raising concerns about misalignment of incentives). Second, DLT saves crypto funds time and fees that would otherwise be incurred for third-party custodians pursuant to the *Advisers Act*. Third, with some exceptions, tokens are taxable only in the case of "recognition events," i.e., if they are exchanged for fiat money. This allows investors to optimize both the timing and the amount of their personal tax liabilities in coordination with their overall portfolios (Mokhtarian & Lindgren, 2018). Finally, the liquidity of tokens lifts venture capital funds' burden to identify and invest in "unicorns" to compensate for the relatively large number of failed projects, because liquid token markets allow crypto funds to exit at any time (Kastelein, 2017).

[4] See https://cryptofundresearch.com/q1-2021-crypto-fund-report/.

3 Theory and hypotheses

3.1 Intuition

Before developing our conceptual framework more formally, we preface the theoretical discussion by stating our two overarching hypotheses and providing some intuition behind them. The first hypothesis, the ***Decentralized Inefficiency Hypothesis*** (***DIH***), posits that search-related frictions render the ICO market relatively inefficient. The second hypothesis, the ***Intermediated Efficiency Hypothesis*** (***IEH***), posits that new DeFi intermediaries, in particular crypto funds, increase ICO market efficiency by reducing search-related frictions. The intuition is simple: the ICO market is very granular; that is, it has high levels of *market participation* (anyone with internet connectivity may participate) and *market completeness* (everything can be tokenized).[5] Smart contracts enable anyone to trade anything with anybody at almost no cost (transactional efficiency). However, smart contracts do not provide technological solutions to facilitate searching for matching transaction counterparties. Therefore, because the number of trading agents and traded claims potentially reaches a maximum in the ICO market and agents bear the burden of finding the agent with the perfectly matching claim for trade, the ICO market may not achieve its welfare potential when many socially optimal trades do not occur if the expected transaction surplus does not compensate for the expected search costs (search-related inefficiency). In the ICO market, these search frictions are plausibly even more pronounced due in large part to the highly asymmetric information and the limits to effective signaling (Hornuf et al., 2021; Momtaz, 2021c). Therefore, a perfectly decentralized

[5] Of course, there are limitations to tokenized market participation and tokenization, such as the technical sophistication that is required from individuals.

ICO market may be relatively inefficient (i.e., the ***DIH***), and reintroducing a certain degree of intermediation improves the market's overall efficiency (i.e., the ***IEH***). The following section introduces the building blocks for our theory and formally derives the hypotheses.

3.2 Search-related frictions and ICO market efficiency

Search-related frictions refer to economic costs stemming from market imperfections that impede the efficient matching of transaction counterparties in decentralized markets (e.g., Duffie et al., 2005). As such, search frictions are proportionate to the degree of market decentralization. In principle, market failure may occur if search costs exceed the welfare arising from the exchange of assets (Weill, 2020). Therefore, the probability of market failure increases in the degree of market decentralization. As we discuss in Sect. 3.3 below, decentralized markets that face salient search-related inefficiency often revert back to intermediated market microstructures, in which intermediaries offer services that reduce search frictions (Gavazza, 2016; Rubinstein & Wolinsky, 1987). The following explains why search frictions in the ICO market are plausibly very pronounced. ICO-specific search frictions include, inter alia, (1) protocol-interface risks, (2) protocol-immanent risks, (3) smart-contract risks, (4) oracle risks, and (5) governance-related risks (Harvey et al., 2021).

The ICO market is prone to search frictions by design, largely because it improves on both *market participation* and *market completeness*. Market participation refers to the number of agents that can access a market. DLT has significantly lowered the entry barriers to entrepreneurial finance markets, inter alia, through a dramatic reduction of the transaction costs for crowdfunding campaigns (demand-side entry barrier) and a reduction in the minimum investment amount thanks to fractional token ownership (supply-side entry barrier) (Bellavitis et al., 2021; Fisch, 2019; Huang et al., 2020; Lambert et al., 2021; Zetzsche et al., 2020). Indeed, Fisch et al. (2022) report that the ICO market has democratized entrepreneurial finance, evidenced, e.g., by the increased number of investors from ethnic minorities (see, also, Butticé and Vismara, 2022; Meoli et al., 2022; Rawhouser et al., 2023). Market completeness refers to the variety of assets in a market. Asset heterogeneity also creates search problems because it is proportionate to the investors' effort required to determine the relative fit of a focal asset in the light of an investor's subjective preferences (Rubinstein & Wolinsky, 1987). Smart contracts have increased asset heterogeneity substantially because they allow the tokenization of any claim. For example, Fisch and Momtaz (2020) report that the ICO market's demand side is very competitive, with often more than 1,000 competing token offerings present at the same time. Given this high intensity, it is evident that market completion exacerbates search frictions.

The high level of asymmetric information in the ICO market further aggravates the search problem for investors (Bellavitis et al., 2020; Block et al., 2021; Fisch, 2019; Hornuf et al., 2021). Asymmetric information is a pervasive problem in entrepreneurial finance (Colombo et al., 2019; Vismara, 2018b). At its core, the problem with asymmetric information is that financial investors lack the information to gauge the true quality of an investment, resulting in equilibrium prices that are based on the population average instead of a more discriminatory pricing mechanism based on the underlying investment value (Jensen & Meckling, 1976; Leland & Pyle, 1977). Consequently, high-quality investments could sell at a discount, deterring issuers from putting those investment opportunities on the market entirely, which may create a market for lemons (Akerlof, 1978). Informational asymmetries are salient in the ICO market, inter alia, because blockchain-savvy entrepreneurs are typically young and lack a track record (An et al., 2019; Fisch, 2019); the tokens sold are for yet undeveloped, future products (Fisch, 2019; Howell et al., 2020; Momtaz, 2020a); there are little mandatory disclosure laws (see Bellavitis et al., 2021; Boreiko et al., 2019); and token issuers are known to embellish the information disclosed in ICO whitepapers (Momtaz, 2021c). These problems increase aggregate uncertainty in the ICO market, which accordingly exacerbates search-related inefficiency.

Finally, search-related inefficiency is also partly driven by the limits to signaling in the ICO market. Several studies argue that the absence of an institutional framework for ICOs may create a moral hazard in signaling (Hornuf et al., 2021; Momtaz, 2021c). For example, Momtaz (2021c, p. 2) argues that "issuers plausibly have an incentive to bias signals of venture quality to their advantage because there currently are neither functioning institutions that verify signals ex ante nor are there those that punish signals ex post once the bias is detected. If investors are attracted to the ventures with the most positive signals and fail to identify biased ones, then firms which are not sending biased signals may experience a competitive disadvantage. This effectively creates a moral hazard in signaling." His argumentation offers an explanation for the large number of fraudulent ICOs and scams (typical estimates are >85%; see, for a more detailed analysis, Hornuf et al., 2021). Therefore, limits to signaling are relevant for the granular ICO market because they intensify search-related frictions. ICO market granularity (i.e., high market participation and completion) is proportionately related to the amount of endogenous signals that investors need to process, which reduces the effort that can be allocated to validate each received signal. As a consequence, a moral hazard in signaling increases search-related market inefficiency by abetting imperfect matches (Momtaz, 2021c; Zetzsche et al., 2020).

> **Hypothesis 1:** Search-related frictions impede the efficiency of the ICO market.

3.3 Intermediation and ICO market efficiency

Specialized intermediaries, so-called crypto funds, are entering the ICO market, as indicated by Fig. 2, which is likely because of the pronounced search frictions, as well as the problems revolving around informational asymmetries and the limits to signaling. Intermediaries have long been known for extracting rents from reducing trading frictions in decentralized markets (Demsetz 1968, Schueffel 2021, and Allen and Santomero 1997 for a more general treatment of financial intermediation). Some (e.g., Zetzsche et al., 2020) even argue that DeFi markets do not reduce intermediation at all, but simply move it to other parts in the financial value chain. There are several reasons as to why intermediation may help reduce search frictions and improve the efficiency of the ICO market.

First, intermediaries directly reduce search frictions. Crypto funds employ specialized teams of DLT-savvy and financial experts, who have both the skills and the resources to screen the market, pre-select suitable investment targets, and then monitor portfolio companies post-investment, as well as employ sophisticated active portfolio management strategies during market shock periods (Fisch & Momtaz, 2020). This reduces retail investors' effort as well as the costs associated with finding matching investments and searching for information about investment quality. Similarly, given that the number of crypto funds is roughly one-tenth of the number of tokenized startups, the ceteris paribus probability that retail investors will approach the best-matching crypto fund is ten times higher than that of them approaching the best-matching tokenized startup. Therefore, intermediation through crypto funds plausibly reduces search frictions in the ICO market dramatically.

Second, intermediaries reduce informational asymmetries in ICOs because they have an incentive and the ability to generate information, as seen in other entrepreneurial finance markets, such as the IPO market (Benveniste & Spindt, 1989). They also have both an incentive and the resources to monitor and produce information (Boreiko & Vidusso, 2019; Tirole, 2001). The role of intermediaries may be more salient in the ICO market than in other, more regulated entrepreneurial finance markets due in large part to its lack of effective public institutions (Zetzsche et al., 2020). In particular, there are by and large no disclosure requirements in the ICO market, as well as hardly any behavioral norms about the informational content required by investors and hence disclosed by token sellers, which results in small amounts of disclosed information, and investors place little trust in voluntarily disclosed information around ICO campaigns (Kastelein, 2017; Zetzsche et al., 2020). Second, intermediaries reduce informational asymmetries in ICOs because they have an incentive and the ability to generate information, as seen in other entrepreneurial finance markets, such as the IPO market (Benveniste & Spindt, 1989). They also have both an incentive and the resources to monitor and produce information (Boreiko & Vidusso, 2019; Tirole, 2001). The role of intermediaries may be more salient in the ICO market than in other, more regulated entrepreneurial finance markets due in large part to its lack of effective public institutions (Zetzsche et al., 2020). In particular, there are by

and large no disclosure requirements in the ICO market, as well as hardly any behavioral norms about the informational content required by investors and hence disclosed by token sellers, which results in small amounts of disclosed information, and investors place little trust in voluntarily disclosed information around ICO campaigns (Kastelein, 2017; Zetzsche et al., 2020).

Third, similarly to the argument above, intermediaries may provide a delegated monitoring function by which investors in the ICO market may delegate monitoring power to intermediaries who then make sure that the employed capital is used as efficiently as possible (Allen & Santomero, 1997; Becht et al., 2003). Delegated monitoring is arguably particularly pronounced in the ICO market, in which fractionalized, tokenized projects can be traded, and retail investors' portfolios may include many tokenized projects, too many for the retail investors to monitor themselves. By delegating the monitoring function to an intermediary, investors can benefit from the intermediary's skills and resources thanks to the economies of scale for large, specialized crypto funds. Similarly, intermediaries may provide a risk management and liquidity transformation function (Allen & Santomero, 1997). That is, crypto funds with specialized market knowledge and investment experience may be better at hedging market risk than individual retail investors. This helps with consumption smoothing. That is, retail investors desire stable flows of income and little exposure to market-wide shocks. In addition, retail investors may hold under-diversified portfolios, given the explosive growth of the ICO market. Investing in crypto funds deals with both issues at the same time: Crypto funds provide active risk management and improve portfolio diversification.

Overall, specialized DeFi intermediaries can help reduce search frictions that are associated with the initial search for investments and the subsequent search for information about the investments' performance and prospects. Unlike individual investors, DeFi intermediaries benefit from economies of scale that allow them to invest in DLT-specific and financial human capital that ultimately leads to a competitive advantage in information production and searching, a service for which they can plausibly extract economic rents.

Hypothesis 2: Crypto funds mitigate search-related frictions in the ICO market.

4 Data and methods

4.1 Data sources

We rely on a sample from the *Token Offerings Research Database* (TORD).[6] The TORD covers more than 6,000 token offerings through December 2020, and provides a linking table to connect each token offering to external data, such as historic token prices from *Coinmarketcap*. We supplement the data with hand-collected variables, such as, in particular, human capital characteristics from *LinkedIn* and institutional investor data from *CryptoFundResearch*.

Given our twofold empirical approach (i.e., juxtaposing reduced-form and structural estimates), we have to construct two distinct samples. The first sample described in Sect. 4.2 is cross-sectional. As such, it resamples the samples in related studies (e.g., Fisch, 2019; Momtaz, 2021c). The final sample consists of 567 token offerings, for which we were able to retrieve all required information.[7] The second, described in Sect. 4.3, is longitudinal and its structure represents a novel approach in the entrepreneurial finance literature. It covers the ICO market's key dimensions at an aggregate level, including 10,470 unique active ICO-month observations and 1,922 completed ICOs. As described in Sect. 7, the longitudinal sample allows for structurally estimating the ICO market model introduced in Sect. 6.

4.2 Cross-sectional sample for regressions

The sample consists of 567 ICOs with complete information. Variables definitions and summary statistics for the cross-sectional sample are below in Sects. 4.2.1 and 4.2.2, respectively.

[6] Retrieved from https://www.paulmomtaz.com/data/tord in June 2021. Other papers that rely on the TORD include, inter alia, Meoli and Vismara (2022), Kreppmeier and Laschinger (2023), and Zhao et al. (2023).

[7] A decrease in sample size with regard to the population size of token offerings is common in the literature. For example, the samples of Benedetti and Kostovetsky (2021) are reduced from 4,441 to 582 and from 2,390 to 283, respectively.

4.2.1 Variables

Dependent variable: time-to-funding The time, in days, between a successful ICO's start and end date. The variable is log-transformed. Duration variables are a viable proxy for trading delays in decentralized search markets (Gavazza, 2016) and the time-to-funding is a common duration variable in the ICO context (e.g., Momtaz, 2020a).

Dependent variable: ICO firm valuation Following existing studies on ICO performance (e.g., Fisch, 2019), we operationalize startup valuation as the logarithmic funding amount in $ acquired during the token offering. The funding amount may be an imperfect proxy for valuation. Therefore, in robustness checks, we demonstrate that non-intermediated ICOs also sell at a discount when measured relatively, e.g., via the funding amount over the hard cap.

Independent variable: intermediated We proxy for whether an ICO was intermediated by checking whether a Crypto Fund (CF) backed an ICO campaign, following Fisch and Momtaz (2020). CF-backed ICOs are coded as one, and zero otherwise. Crypto funds are not intermediaries in a matchmaking sense, they are institutional investors that intermediate by pooling individual investors' funds and employ sophisticated venture market screening and investment strategies to employ their clients funds as good as possible.

Control Variables: Venture Characteristics

Team size. The number of team members, which is a first-order determinant of success in token offerings (Fisch, 2019; Momtaz, 2020a).

Technical experience. This is the percentage of team members with a technical background, which might by relevant in a tech-heavy context like ICOs (Colombo et al., 2021). The variable is hand-collected from team members' professional network profiles, such as *LinkedIn*.

Crypto experience. This is the percentage of team members with a background in crypto, which might by relevant in a crypto-specific setting like ICOs (Colombo et al., 2021). The variable is hand-collected from team members' professional network profiles, such as *LinkedIn*.

Ph.D. This is the percentage of team members that hold a Ph.D. degree, which may be relevant because ICOs are technologically sophisticated and require therefore a certain amount of human capital, which a Ph.D. degree may signal (Colombo et al., 2021). The variable is hand-collected from team members' professional network profiles, such as *LinkedIn*.

Rating. The overall project rating based on the consensus of industry experts on ICObench, and is an important predictor of success in token offerings (Bellavitis et al., 2020; Fisch, 2019; Momtaz, 2020a). The scale runs from 1 ("low quality") to 5 ("high quality").

Control Variables: Offering Characteristics

Soft cap. A dummy variable for whether the startup has announced a soft cap in its token offering. A soft cap is the minimum funding amount at which the offering is deemed successful, and funding campaigns that fail to reach the soft cap typically redeem investor money and end the project (Fisch, 2019).

Hard cap. A dummy variable for whether the startup has announced a hard cap in a token offering. A hard cap is the funding amount that a startup requires to be "fully" funded (Fisch, 2019).

KYC. This is a dummy variable that is equal to one if the ICO involved a Know-Your-Customer (KYC) process, and zero otherwise. It is important to control for KYC because it may partially substitute for intermediaries' information production function on the sell side (Fisch & Momtaz, 2020).

Pre-sale. A dummy variable indicating if the actual token offering was preceded by a pre-sale event. Presales may be relevant because they can also substitute for intermediaries' information production function on the sell side by facilitating the "bookbuilding" (Fisch & Momtaz, 2020).

Whitelist. A dummy indicating if the token offering has an active whitelist. Whitelists may perform similar functions as KYC processes.

 # competing offerings. This is the number of competing ICOs, that is, ICOs whose offering period overlaps with that of the focal ICO. The number of competing ICOs is relevant because in bull markets the number of ICOs can soar and intermediaries may help reducing search effort for individuals in these "ICO thickets" (Bellavitis et al., 2020; Fisch & Momtaz, 2020).

ERC20. A dummy variable for whether the token offering relies on the technical ERC20 standard. A technological standard may reduce the need for (technological) certification by an intermediary (Cumming et al., 2023; Fisch & Momtaz, 2020).

Fixed effects. Quarter-year and country fixed effects are always included to absorb time-varying and jurisdictional variation.

4.2.2 Summary statistics

Summary statistics for the cross-sectional sample are in Table 1, grouped by key variables, ICO-related characteristics, and team-related characteristics. As per the key variables, 8.5% of all sample ICOs are intermediated, the average (median) ICO firm takes 45 (55) days to successfully complete the crowdfunding campaign, and it achieves an average (median) valuation of $9.3 million ($3.5 million). Apparently, the valuation proxy is positively skewed, which has important implications for our modeling choices in Sect. 4. Further, 8.5% of all startups have institutional investor backing and 89.1% build their tokens on the Ethereum blockchain (e.g., the *ERC20* technical standard). As per the ICO-related variables, 73.7% conduct a pre-sale, 78.3% have a Know-Your-Customer (KYC) process in place, almost all have a whitelist, the average (median) hard cap is $139 million ($19 million), the average (median) soft cap relative to the hard cap amounts to 43% (15%), and the average (median) ICO competes with 947 (875) concurrent campaigns. As per the team-related characteristics, the average (median) ICO startup company receives a rating from industry experts of 3.6 (3.7) on a scale from 1 (low quality) to 5 (high quality), has 15.2 team members, of which 2.3%, 0.4%, and 3.9% are graduates from a technical degree program (e.g., engineering or computer science), hold a Ph.D., and have worked in the crypto industry prior to joining the startup, respectively.

Table 1 also reports the differences in sample means and sample medians to the corresponding TORD-population moments in the last two columns. The differences are mostly significant. Therefore, we weight our regression coefficients to be proportionate to the population moments, as described in Sect. 5 below.

4.3 Longitudinal sample for structural estimation

The sample consists of 10,470 monthly ICOs observations and 1,922 completed ICOs with available price and platform size information. Variables definitions and summary statistics for the longitudinal sample are below in Sects. 4.3.1, 4.3.2 and 4.3.3, respectively.

4.3.1 Variables: quantity panel of ICO market activity per month (# monthly obs. = 10,470)

ICO firms' platform size, in # users. The number of *Twitter* followers serves as a proxy for an ICO firm's underlying platform or network size. It is expressed as the average over all active ICOs in a given month.

Active ICOs. The number of active ICOs in a given month, that is, ICOs which are currently open to receiving crowdfunding contributions in exchange for tokens.

Completed non-intermediated ICOs. The number of non-intermediated ICOs that are successfully completed in a given month and not backed by an intermediary.

Completed intermediated ICOs. The number of non-intermediated ICOs that are successfully completed in a given month and backed by an intermediary.

Intermediaries' cumulative token inventory. The cumulative number of ICO backings by intermediaries in per month.

4.3.2 Variables: price panel (# completed ICOs = 1,922)

Token prices in non-intermediated ICOs. The average total token price (analogue to the ICO firm valuation) in ICOs that are not intermediated. This value is observed.

Token prices in intermediated ICOs. The average total token price (analogue to the ICO firm valuation) in ICOs that are not intermediated. This value is imputed from the token price discount that intermediaries can plausibly demand, based on the second-stage regressions in Table 4. The method is explained further below.

ICO firms' platform size, in # users. The number of *Twitter* followers serves as a proxy for an ICO firm's underlying platform or network size. It is expressed as the average over completed ICOs during the 2017–2020 period.

4.3.3 Summary statistics

Summary statistics for the longitudinal sample are in Table 2. The longitudinal sample reflects demand and supply dynamics in the ICO market as a whole. Panel A describes aggregated statistics for token quantity moments per month. A token offering enters the monthly panel as soon as the startup starts selling tokens and exits the panel in the month in which the campaign ends. This leads to 10,470 offering-month

Table 1 Summary statistics for cross-sectional sample — ICOs, 2017–2020

	Sample (# obs. = 567)					**Δ to TORD-Population**	
	Mean	SD	Q1	Median	Q3	Δ Mean	Δ Median
Key variables:							
Intermediated	0.085	0.279	0	0	0	0.023*	0
ICO duration to achieve funding goal, in days (log.)	3.799	1.090	3.401	4.007	4.522	0.110**	0.294***
Valuation, in $ mil.	9.253	27.448	1.054	3.500	10.192	−2.727*	−0.286
ICO-related characteristics:							
Ethereum	0.891	0.312	1	1	1	0.019	0
Pre-sale	0.737	0.441	0	1	1	0.244***	1***
# competing offerings	947	439	664	875	1,175	176.46***	152***
KYC process	0.783	0.413	1	1	1	0.367***	1***
Hard cap, in $ mil.	139	978	9	19	32	−76	−1
Soft cap in % of hard cap	0.43	7.17	0.07	0.15	0.27	−0.429***	−0.15***
Whitelist	0.99	0.00	1	1	1	0.57***	1***
Team-related characteristics:							
Expert rating	3.641	0.538	3.300	3.700	4.000	0.720***	0.800***
# team members	15.2	7.5	10	15	19	4.5***	6***
% team with technical degree	0.023	0.050	0.008	0.014	0.025	−0.231***	−0.216***
% team with crypto experience	0.039	0.084	0.014	0.023	0.040	−0.318***	−0.311***
% team with Ph.D.	0.004	0.008	0	0	0.004	−0.045***	0

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

Table 2 Summary statistics for longitudinal sample — ICO market dynamics, 2017–2020

	Mean	SD	Q1	Median	Q3
Panel A: Quantity Panel of ICO Market Activity per Month (# monthly obs. = 10,470)					
ICO firms' platform size, in # users	28,431	136,751	1,034	1,388	9,366
Active ICOs	360	161	240	359	520
Completed non-intermediated ICOs	348	154	237	357	513
Completed intermediated ICOs	12.2	9.6	2	14	21
Intermediaries' cumulative token inventory	248	91	190	283	320
Panel B: Price Panel (# completed ICOs = 1,922)					
Token prices in non-intermediated ICOs	12.98	21.35	1.00	4.00	15.00
Token prices in intermediated ICOs	6.22	12.85	0.43	1.71	6.41
ICO firms' platform size, in # users	8,334	26,278	774	2,788	7,569

observations for the 2017–2020 period. Each month an average of 360 (SD = 161) startups raise finance by selling tokens. Thereof, 348 (SD = 154) are not intermediated, while 12.2 (SD = 9.6) are intermediated. The cumulative intermediated market volume or the intermediaries' cumulative token inventory, measured as the cumulative number of intermediated ICOs, is 248 (SD = 91). As for ICO firms' platform or network size, the average startup has a followership on *Twitter* (our main proxy for network size) of 24,430 (SD = 136,751) accounts, although the range is substantial (Q1 = 1,034; Q3 = 9,366), indicating pronounced positive skewness. We will use this feature for identification of our model below.

Panel B of Table 2 shows price-related summary statistics for the longitudinal sample, which is based on all completed token offerings over the 2017–2020 period with available information on token valuation and network size. This results in a sample of 1,922 token offerings. Tokens in non-intermediated ICOs are, on average, valued at \$12.98 million in total (SD = \$4.00 million), while intermediaries are able to purchase them at a discount (see Sect. 5.3), resulting in aggregate prices of \$6.22 million (SD = \$1.71 million). The average ICO firm's platform size in these transactions amounts to 8,334 (SD = 26,278) individuals.

5 Regression results

The goal in this section is twofold. The first objective is to estimate the causal effect of ICO intermediation on the time to achieve a crowdfunding goal (i.e., the proxy for search frictions). While the expected effect is negative because intermediaries plausibly help reduce search frictions, the empirical relation is not free of endogeneity concerns. Specifically, it is possible that only ICOs with strong success prospects are able to secure intermediation services, which could be confounding any negative regression coefficient (i.e., a selection effect), rather than that intermediation being the reason as to why those ICOs are able to achieve their funding goals in a shorter time period (i.e., the treatment effect). The second objective is to estimate the causal relation between ICO intermediation and token valuation. In particular, in the spirit of the growing body of anecdotal evidence that intermediaries are able to extract significant economic rents in the form of token discounts for their services (estimates often range between 50 and 70%),[8] the goal is to estimate the token value discounts that ICOs that are not able to secure intermediation services incur. Endogeneity issues might bias the expected negative, empirical relation between token valuation and non-intermediation if low-quality issuers' tokens trade at a discount because they are low-quality and therefore unable to secure intermediation services, rather than because they lack intermediation in the first place.

Given these identification threats, we outline the econometric approach to debias the regression models in Sect. 5.1, and present debiased regression results for the relation between intermediation and ICO duration

[8] See, e.g., https://icodrops.com/pre-sales/, https://www.cointelligence.com/content/private-sales-icos/, https://medium.com/applicature/private-sale-or-public-sale-b515476718a3, all retrieved on February 24, 2022.

in Sect. 5.2, and for the impact of non-intermediation on token value discounts in Sect. 5.3.

5.1 Econometric specification: two-stage approaches to mitigate endogeneity

Several two-stage approaches help mitigate concerns about potential endogeneity pertaining to sample selectivity,[9] In particular, our approach to debias the treatment effects of intermediation mitigates selection based on unobservables, which are potentially pronounced confounders in entrepreneurial finance.[10]

The general approach is to estimate a first-stage model that predicts the probability that an ICO is intermediated or non-intermediated. These "selection probabilities" are then transformed and included in the second-stage models, which estimate the treatment effects. Specifically, we are interested in two distinct treatment effects; namely, the treatment effect of intermediation on the time it takes ICO firms to achieve their crowdfunding goals and the treatment effect of the lack of intermediation on token valuation. Equations 1 and 2 represent the potentially confounded OLS models:

$$\text{ICO duration}_i = \beta \times \mathbb{1}_{\text{Intermediated}_i} + \Omega_i \gamma + \varepsilon_i \tag{1}$$

$$\text{Token valuation}_i = \beta \times \mathbb{1}_{\text{Non-intermediated}_i} + \Omega_i \gamma + \varepsilon_i \tag{2}$$

where i indexes ICOs, $\mathbb{1}_{\text{Intermediated}_i}$ and $\mathbb{1}_{\text{Non-intermediated}_i}$ represent indicator variables for whether or not ICO i is intermediated, and Ω_i represents a vector of control variables.

For the models in Eqs. 1 and 2 to estimate an unbiased treatment effect of ICOs' intermediation status, it is necessary to assume that the independent variables are orthogonal to the error term, i.e., $E[\Omega_i, \varepsilon_i] = 0$. This condition is violated if selectivity is present; for example, in the case that only high-quality ICOs are able to secure intermediation services. Therefore, the first stage explicitly models the selective matching between ICO firms and intermediaries. Specifically, we predict that ICO i is intermediated, $\mathbb{1}_{\text{Intermediated}_i}$, by a vector of exogenous control variables that possibly influence the selection mechanism, $\Omega_i^{(s)}$:

$$\mathbb{1}_{\text{Intermediated}_i} = \Omega_i^{(s)} \delta + \xi_i \tag{3}$$

Estimates from Eq. 3 help control for unobserved heterogeneity as follows. We use Generalized Residuals (GRs) both as explicit controls for selection-based endogeneity, and as instrumental variables for ICOs' intermediation status (Gourieroux et al., 1987), which controls for unobserved heterogeneity by explicitly modeling any endogeneity in the error term, defined as follows:

$$GR_i = \mathbb{1}_{\text{Intermediated}_i} \times \frac{\phi\left(-\Omega_i^{(s)}\delta\right)}{1 - \Phi\left(-\Omega_i^{(s)}\delta\right)} + \left(1 - \mathbb{1}_{\text{Intermediated}_i}\right) \times \frac{-\phi\left(\Omega_i^{(s)}\delta\right)}{\Phi\left(-\Omega_i^{(s)}\delta\right)} \tag{4}$$

where $\phi(.)$ and $\Phi(.)$ denote the probability density and the cumulative density functions of the standard normal distribution, respectively. We restrict the standard deviation of the error term for intermediated ($\sigma_{\varepsilon},\ \mathbb{1}_{\text{Intermediated}_i}$) to be equal to that of non-intermediated ICOs ($\sigma_{\varepsilon}, \mathbb{1}_{\text{Non-intermediated}_i}$). The restriction ensures that GR_i can be added as an instrumental variable to Eq. 1.

For Eq. 2, the adjustments are identical, with the exception that "selection probabilities" are estimated for the case that ICO i is not intermediated, i.e., $\mathbb{1}_{\text{Non-intermediated}_i}$.

5.2 Regression results: intermediation and ICO duration

Table 3 shows the regression results for how ICO intermediation impacts ICO duration. All models include quarter-year and country fixed effects to absorb both time-related and geographical variation. All reported standard errors are robust. The selection model for Eq. 3 is in column (1), with an indicator variable for

[9] The techniques used in our study have been employed before in similar contexts (e.g., Fisch and Momtaz 2020; Bertoni et al., 2011; Colombo et al., 2010; Colombo et al., 2021; Cumming et al., 2023).

[10] For example, unobserved heterogeneity in startups' time-to-funding by venture capitalists can be so pronounced that it biases common time-to-event models (Momtaz, 2021b)

Table 3 Two-stage analysis of search frictions in intermediated vs. non-intermediated ICOs

Stage: *Model:* *Dependent variable:*	1st Selection $\mathbf{1}_{\text{Intermediated}}$	1st Control Duration	2nd GR Duration	2nd IV Duration
Key variable:				
$\mathbf{1}_{\text{Intermediated}}$		−0.273***	−0.273***	−0.287***
		(0.076)	(0.077)	(0.079)
ICO-related controls:				
Ethereum	0.030	−0.032	−0.032	−0.032
	(0.041)	(0.069)	(0.069)	(0.069)
Pre-sale	−0.013	0.090*	0.090*	0.090*
	(0.030)	(0.050)	(0.050)	(0.050)
# competing offerings (log.)	−0.098**	2.616***	2.616***	2.615***
	(0.039)	(0.066)	(0.066)	(0.066)
Soft cap, in \$ mil. (log.)	−0.001	−0.268***	−0.268***	−0.268***
	(0.041)	(0.068)	(0.068)	(0.068)
Hard cap, in \$ mil. (log.)	−0.006	0.007	0.007	0.007
	(0.009)	(0.015)	(0.015)	(0.015)
Whitelist	0.036	−0.038	−0.038	−0.038
	(0.026)	(0.044)	(0.044)	(0.044)
KYC	−0.007	−0.027	−0.027	−0.027
	(0.033)	(0.054)	(0.054)	(0.054)
Team-related controls:				
Expert rating	0.023	−0.015	−0.015	−0.014
	(0.026)	(0.043)	(0.043)	(0.043)
# team members	0.001	−0.001	−0.001	−0.001
	(0.002)	(0.003)	(0.003)	(0.003)
% team with technical degree	0.207***	−0.154	−0.154	−0.151
	(0.078)	(0.130)	(0.131)	(0.130)
% team with rypto experience	0.008	0.042	0.042	0.042
	(0.064)	(0.106)	(0.106)	(0.106)
% team with Ph.D.	0.348*	−0.784***	−0.784***	−0.779***
	(0.177)	(0.295)	(0.297)	(0.296)
Population weights	✓	✓	✓	✓
Generalized Residuals	✗	✗	✓	✗
Instrumental Variable	✗	✗	✗	✓
Country fixed effects	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓
# Obs.	567	567	567	566
Adjusted R^2	0.018	0.823	0.823	0.823

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

whether an ICO is intermediated as the dependent variable. Our baseline regression results for Eq. 1 are presented in column (2), with the natural logarithm of the time between ICO start and end in days as the dependent variable. The second-stage regression results are shown in columns (3) and (4), with the generalized residual, as measured in Eq. 4, as an added control and as an instrumental variable for the intermediation indicator, respectively. In particular, these approaches outperform matching-on-observables in our context because they do not require ICO intermediation to be independent of unobserved factors and the marginal probability of ICO intermediation does not need to equal the average probability. Finally, given the sample population differences reported in Table 1, we weight all regression coefficients by the inverse of the (absolute value) sum of relative deviations from population means for each token offering to move our estimates of the local treatment effect in our sample closer to the average treatment effect in the population of ICOs.

The results suggest that the effect of ICO intermediation on ICO duration is significantly negative throughout all models in columns (2) to (4). The coefficients range from −0.273 to −0.287, statistically highly significant with p-values consistently below 1%. The similarity of these coefficients may imply that selectivity does not significantly bias the causal effect of ICO intermediation on ICO duration. Indeed, the adjusted R^2 for the selection model in column (1) is relatively low (1.8%). Overall, the marginal effect of ICO intermediation on ICO duration is a relative decrease in the time it takes for intermediated ICO firms to achieve their crowdfunding goals of −24.9% (exp(−0.287)–1). This strongly supports the overarching hypothesis that intermediaries help reduce search frictions in the ICO market.

For the selection model, the coefficients of the control variables largely show plausible effects, suggesting that (i) the number of competing offerings is negatively associated with the probability of ICO intermediation, while (ii) the relative amount of team members with a technical background or (iii) a Ph.D. degree have positive effects.

For the key models in columns (2) to (4), the coefficients of the control variables also appear plausible, suggesting that (i) pre-sales and (ii) the number of competing offers increase the time it takes ICO firms to achieve the crowdfunding goal, while (iii) the size of the soft cap and (iv) the percentage of team members with a Ph.D. degree decrease the duration. It is noteworthy that the coefficients of the control variables are consistent in terms of both the signs and the magnitudes across columns (1) to (3).

Overall, the results in Table 3 suggest that ICO firms have an economic motive to secure intermediation for their offerings to reduce their time-to-funding.

5.3 Regression results: lack of intermediation and discount on token value

Table 4 presents regression results for the effect of ICO intermediation on token valuations. In particular, we test whether tokens offered in non-intermediated ICOs trade at a relative discount. The tests are similar to those in Table 3, with the difference that the dependent variables are replaced for an indicator variable for non-intermediated ICOs in column (1) and the natural logarithm of token valuations in \$ million in columns (2) to (4). The models also include quarter-year and country fixed effects, and the standard errors are robust. Columns (3) and (4) show second-stage regressions that control for unobservable heterogeneity by controlling for the generalized residuals in column (3) and for instrumenting the indicator variable for non-intermediated ICOs with the generalized residuals in column (4).

The results suggest that tokens offered in non-intermediated ICOs trade at a significant discount. Specifically, the average non-intermediated ICO offers tokens at a discount of up to −57.7% (exp(−0.861)–1) in the IV model in column (4). The coefficient estimates for our key variable ranges from −0.793 to −0.861, which are highly statistically significant, with p-values consistently below 1%. It is noteworthy that the key coefficient of the control model (−0.793) is clearly different from that in the GR and IV models (−0.850 and −0.861, respectively), indicating that the selection of intermediated vs. non-intermediated ICOs would underestimate the token valuation effect in the absence of the adjustments in columns (3) and (4).

Note that the adjusted R^2 is similarly high as in related studies (Bellavitis et al., 2020; Fisch, 2019), and the control variables also seem to be consistent. Specifically, (i) expert ratings, (ii) soft cap amounts, (iii) hard cap amounts, (iv) whitelists, (v) the number of ICO team members, and (vi) the relative amount of team members with prior crypto industry experience are positively related to ICO token valuations. In contrast, (vii) only the percentage of technical team members has a negative effect. These estimates are consistent across all model specifications in columns (2) to (4).

Overall, the non-intermediated ICOs offer tokens at dramatic ceteris paribus discounts of up to −57.7%,

Table 4 Two-stage analysis of valuation discount in non-intermediated ICOs

Stage: *Model:* *Dependent variable:*	1st Selection $1_{\text{Not intermediated}}$	1st Control Valuation	2nd GR Valuation	2nd IV Valuation
Key variable:				
$\mathbf{1}_{\text{Not intermediated}}$		−0.793***	−0.850***	−0.861***
		(0.262)	(0.262)	(0.274)
ICO-related controls:				
Ethereum	−0.030	−0.031	−0.011	−0.033
	(0.041)	(0.236)	(0.236)	(0.237)
Pre-sale	0.013	−0.207	−0.250	−0.206
	(0.030)	(0.172)	(0.173)	(0.172)
# competing offerings (log.)	0.098	−0.293	−0.278	−0.287
	(0.039)	(0.226)	(0.225)	(0.227)
Soft cap, in $ mil. (log.)	0.001	0.561**	0.571**	0.562**
	(0.041)	(0.233)	(0.232)	(0.233)
Hard cap, in $ mil. (log.)	0.006	0.431***	0.439***	0.432***
	(0.009)	(0.051)	(0.051)	(0.051)
Whitelist	−0.036	0.253*	0.268*	0.250*
	(0.026)	(0.150)	(0.150)	(0.151)
KYC	0.007	−0.083	−0.068	−0.082
	(0.033)	(0.187)	(0.187)	(0.188)
Team-related controls:				
Expert rating	−0.023	0.347**	0.348**	0.345**
	(0.026)	(0.149)	(0.148)	(0.149)
# team members	−0.001	0.038***	0.036***	0.038***
	(0.002)	(0.010)	(0.010)	(0.010)
% team with technical degree	−0.207***	−1.533***	−1.663***	−1.547***
	(0.078)	(0.448)	(0.450)	(0.448)
% team with crypto experience	−0.008	0.970***	0.993***	0.970***
	(0.064)	(0.365)	(0.364)	(0.366)
% team with Ph.D.	−0.348*	1.242	1.420	1.218
	(0.177)	(1.018)	(1.018)	(1.019)
Population weights	✓	✓	✓	✓
Generalized Residuals	✗	✗	✓(-**)	✗
Instrumental Variable	✗	✗	✗	✓
Country fixed effects	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓
# Obs.	567	567	567	566
Adjusted R^2	0.018	0.264	0.269	0.262

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

which is consistent with anecdotal evidence that reports discounts in the range of 50 to 70%. This implies that the average non-intermediated ICO issuer "leaves money on the table" to the amount of $5.34 million. By implication, the causal nature of these results suggests that, in competitive DeFi markets, intermediaries can charge very high fees commensurate with the estimated discounts for their intermediation services, an interpretation that we will use to identify our theoretical model below.

To summarize the reduced-form evidence in Sects. 5.2 and 5.3, ICO intermediation is causally related to the time it takes ICO firms to achieve their crowdfunding goals and token valuation discounts, respectively. Therefore, the results offer initial supporting evidence for the overarching conjectures that intermediation helps reduce search frictions in ICO markets, and intermediaries can charge substantial fees for their services.

Table 5 Post hoc analyses: second-stage regression results for different subsamples

Dependent variable:	**Funding amount, in USD (log.)**		**ICO duration, in days (log.)**	
Panel A: Market phases				
	Bull market	**Bear market**	**Bull market**	**Bear market**
$\mathbf{1}_{\text{Not intermediated}}$	−1.637**	−0.713**	0.056	0.282***
	(0.720)	(0.287)	(0.391)	(0.064)
Panel B: Team quality				
	Above-median team rating	**Below-median team rating**	**Above-median team rating**	**Below-median team rating**
$\mathbf{1}_{\text{Not intermediated}}$	−0.771**	−0.537	0.435***	0.277**
	(0.318)	(0.472)	(0.130)	(0.127)
Panel C: Product quality				
	Above-median product rating	**Below-median product rating**	**Above-median product rating**	**Below-median product rating**
$\mathbf{1}_{\text{Not intermediated}}$	−0.767**	−0.427	0.448***	0.167
	(0.329)	(0.489)	(0.134)	(0.129)
Panel D: Venture's vision quality				
	Above-median vision rating	**Below-median vision rating**	**Above-median vision rating**	**Below-median vision rating**
$\mathbf{1}_{\text{Not intermediated}}$	−0.712**	−0.763*	0.494***	0.034
	(0.318)	(0.418)	(0.123)	(0.128)
Panel E: Entrepreneurial incentivization (token retention)				
	Above-median token retention	**Below-median token retention**	**Above-median token retention**	**Below-median token retention**
$\mathbf{1}_{\text{Not intermediated}}$	−0.833	−0.838***	0.043	0.351***
	(0.547)	(0.299)	(0.108)	(0.126)
Model information:				
Other controls	✓	✓	✓	✓
Population weights	✓	✓	✓	✓
Generalized Residuals	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

5.4 Post hoc analyses and robustness checks

The identified effects of ICO intermediation might differ in various subsamples, and investigating the sensitivity of the main effects may yield additional insights (Newbert et al., 2022). Table 5 shows re-estimated second-stage treatment effects based on the GR model for subsamples based on five different categories, with an indicator variable for non-intermediated ICOs. Panel A shows the main effects for bull or stable versus bear phases in the ICO market. The results suggest that the valuation effect is more pronounced in bull markets and the duration effect is more pronounced in bear markets. Panel B, C, and D show the main effects for above- and below-median subsamples based on *ICObench*'s team, product, and venture vision ratings. The results indicate that the valuation and duration effects are more pronounced for above-median quality firms. Panel C shows the main results for above- and below-median firms based on their token retention ratios. Retaining more tokens is often regarded as a costly signal of firm quality and associated with stronger entrepreneurial incentivization (e.g., Leland and Pyle, 1977). The findings suggest the valuation and duration effects are more pronounced for the below-median token retaining firms.

Further, several additional ad hoc checks confirm the results' robustness. In particular, the results are robust to (i) excluding soft cap and hard cap controls from the regressions, (ii) adding hype-related variables as controls, such as monthly *GoogleTrends* for ICO, blockchain, and cryptocurrency search terms, (iii) controlling for project size in absolute (i.e., the total token supply multiplied by the ICO token price) and relative (i.e., the project size as the number of tokens sold divided by the total token supply) terms, and (iv) adjusting the soft cap and hard cap variables by hypothetical investment amounts by crypto funds in the amount of 10%, 25%, and 50%. Moreover, we also disaggregate the ICO intermediation variable into whether the crypto fund's investment strategy resembles more venture capital or hedge funds and whether the crypto fund's investment strategy follows a specialized or a diversified strategy. While these results lack statistical power due to small sample sizes given the granular subcategories, they are nevertheless qualitatively consistent with the main results and show that crypto hedge funds and diversified funds have a stronger effect on valuation, while crypto venture funds and specialized funds have a stronger effect on ICO duration. Finally, we replace the funding amount as the proxy for ICO firm valuation with a relative measure (actual funding divided by hard cap), which leads to a statistically highly significant coefficient on the indicator for non-intermediated ICOs of -0.179, confirming the main results on the ICO firm valuation discount in the absence of ICO intermediation.

6 Model

6.1 Setup: the ICO market

Any model is an abstraction from reality. Our model faces the additional constraint that we want to structurally estimate it. This requires further abstraction and may come at the cost of ignoring interesting features of the ICO market that can be considered in a purely theoretical model, such as that by Wang et al. (2022). We model the ICO market as a decentralized search-and-bargaining market populated by *individual investors* and *intermediaries* who discount the future at rate $\rho > 0$. The key difference between the two investor types is that only individual investors derive utility from holding tokens (e.g., the token may be used as a membership fee for a video gaming online community, or to purchase cloud storage to save electronic files, or for any other purpose), while intermediaries act as institutional investors that extract economic rents from exploiting market imperfections. The model is set in continuous time with an infinite horizon.[11]

Individual investors (henceforth, **individuals**) are assumed to be risk neutral. At every instant, a mass μ of high-valuation individuals with token valuation $z_h > 0$ enters the ICO market. Their valuation drops to $z_l < z_h$ and they become low-valuation individuals with intensity λ, obeying a continuous-time Markov chain. Because individuals' valuations are independent, there is a mass of $\frac{\mu}{\lambda}$ high-valuation individuals in steady state.

Intermediaries (indexed by d for "middlemen") enter the ICO market as an (endogenous) mass μ_{d}, and we assume that market entry is free. $\mu_{\mathrm{do}}(a)$ and $\mu_{\mathrm{dn}}(a)$ denote the endogenous masses of intermediated and

[11] Weill (2020) offers an excellent overview of related work on search theory. Our analysis follows Gavazza (2016), combining elements from Duffie et al. (2005), Rubinstein and Wolinsky (1987).

non-intermediated ICOs of a platform of size a, respectively. We discuss the role of platform size below. Because intermediaries do not enjoy utility from holding utility tokens, they serve as potential transaction parties independent of any token-valuation parameter.[12] Intermediaries have operating costs k.

Tokens We assume that entrepreneurs launch ICOs such that tokens enter the market at every instant as a mass of $x < \mu$ and transacts at endogenous price p^*. Tokens are heterogeneous with respect to their underlying platform size and are generically ranked, such that $a = 1...100$ ($1 =$ largest platform percentile, $100 =$ smallest platform percentile). Token value decreases in a and has a salvage value $s \geq 0$. A worthless token can also be scrapped free-of-charge at any point in time. Platform size matters because it relates to network effects, which ultimately determine token value (Chen & Bellavitis, 2020; Fisch, 2019). We require $\frac{\mu}{\lambda} > A$, where A represents the total amount of platform tokens in the market, so that, in a Walrasian market, the marginal token-holder is of the high-valuation type. Instantaneous flow utility $\pi(z, a)$ is a function of a token's platform size a and its holder's valuation z. Utility is increasing in valuations ($\pi(z_h, a) > \pi(z_l, a)$), decreasing in token's platform size ranking ($\frac{\partial \pi(z,a)}{\partial a} < 0$) (i.e. smaller platform, lower token value), and it has negative z-a complementarity such that $\frac{\partial \pi(z_h,a)}{\partial a} < \frac{\partial \pi(z_l,a)}{\partial a}$.

Search Individuals pay a search-related costs c_s to find token transaction parties at pairwise independent Poisson arrival rates $\gamma > 0$. Therefore, an individual wishing to sell a token meets a potential buyer at rate $\gamma_s = \gamma \mu_b$, and an individual looking to buy a platform-size-a token meets a potential seller at rate $\gamma_b(a) = \gamma \mu_s(a)$. The masses μ_b and $\mu_s(a)$ are determined in equilibrium. Similarly, individuals meet intermediaries at pairwise independent Poisson arrival times with intensity $\gamma' > 0$. An individual wishing to purchase a platform-size-a token meets a platform-size-a token-holding institutional at rate $\gamma_{bd}(a) = \gamma' \mu_{do}(a)$, and intermediaries meet individuals to sell their tokens at rate $\alpha_{ds} = \gamma' \mu_b$. The sum of $\gamma_{bd}(a)$ and α_{ds} represents the combined search intensity at which buying individuals and selling intermediaries meet. Similarly, γ_{sd} and $\alpha_{db}(a)$ express the search intensities with which selling individuals meet intermediaries and buying intermediaries meet individuals wishing to sell platform-size-a tokens.

Bargaining Meetings between matching buying and selling individuals or with intermediaries lead to price negotiations according to a generalized Nash bargaining framework. The parameters $\theta_s \in \{0, 1\}$ and $\theta_d \in \{0, 1\}$ denote the relative bargaining power of the seller in a non-intermediated ICO and of the institutional in an intermediated ICO, respectively. Thus, we assume symmetric information about token quality, which is why we estimate the model based on residual prices after controlling for determinants of token value other than platform size in Sect. 7.

6.2 Value functions

6.2.1 Individual investors

We distinguish four types of individual investors in our model. Individuals can have a high (z_h) or low (z_l) token valuation, and own or do not own the respective token. Further, individual investors who own a token decide between keeping or selling it, while individual investors who do not hold a token decide between actively trying to purchase tokens in the market or not.

An individual with valuation z holding a platform-size-a token continuously chooses between keeping or selling the asset. If she is not seeking to sell the token, she enjoys utility $\pi(z, a)$ from holding a high-valued token. Her valuation switches to $z_l < z_h$ at rate λ, at which point she faces the decision problem of choosing between the utility from a low-valued token and the proceeds from selling it ($\max\{U_{lo}(a), S_{lo}(a)\}$). Finally, she may incur a capital change in the amount of $U'_{ho}(a)$, which defines her value function as: $\rho U_{ho}(a) = \pi(z_h, a) + \lambda\big(V_{lo}(a) - U_{ho}(a)\big) + U'_{ho}(a)$. Alternatively, she may actively try to sell the token. She also enjoys the current flow utility $\pi(z_h, a)$, faces the decision problem $\max\{U_{lo}(a), S_{lo}(a)\}$ when her valuation drops, and sustains capital change due to network effects $U'_{ho}(a)$. Moreover, she faces the flow search cost c_s. She meets potential buyers at rate γ_s, at which point

[12] Intermediaries do not invest in more than one platforms at once. This assumption largely simplifies the model, and corresponds closely to statistics about institutional investor involvement in the ICO market, e.g., Fisch and Momtaz (2020).

she has to decide between selling the token at price $p(a)$ and becoming a high-valuation non-holder with value V_{hn}, or keeping it. Selling it results in the capital gain $p(a) + V_{hn} - S_{ho}(a)$. Similarly, she meets investors at rate γ_{sd}, at which point she has to decide whether to accept the investor's bid price $p_B(a)$. Thus, her value function satisfies the following Bellman equation: $\rho S_{ho}(a) = \pi(z_h, a) - c_s + \lambda\big(V_{lo}(a) - S_{ho}(a)\big) + \gamma_s \max\{p(a) + V_{hn} - S_{ho}(a), 0\} + \gamma_{sd} \max\{p_B(a) + V_{hn} - S_{ho}(a), 0\} + S'_{ho}(a)$.

Low-valuation token-holding individuals can also choose between keeping and selling the asset. In the former case, because z_l is an absorbing state and valuations cannot switch anymore, her value function satisfies: $\rho U_{lo}(a) = \pi(z_l, a) + U'_{lo}(a)$. In the latter case, the conditions for the value function follow from the fact that z_l is an absorbing state: $\rho S_{lo}(a) = \pi(z_l, a) - c_s + \gamma_s \max\{p(a) + V_{ln} - S_{lo}(a), 0\} + \gamma_{sd} \max\big\{p_B(a) + V_{ln} - S_{lo}(a), 0\big\} + S'_{lo}(a)$.

Individuals who do not own tokens can either passively remain in their ownership status or actively try to purchase tokens in the ICO market. High-valuation individuals who neither hold a token nor are actively trying to purchase one in the market have zero utility: $\rho U_{hn} = 0$. High-valuation individuals who do not hold a token but are actively looking to purchase one in the ICO market pay a search cost c_s and incur a capital loss of $V_{ln} - S_{hn}$ when their valuation drops. Because they cannot be ex-ante sure of the ultimate platform size a that is up for sale when the individual encounters a potential transaction partner, but which is highly value-relevant, they take the expectations over all platform sizes. They meet a selling individual at rate $\gamma_b(a)$ and a selling investor at rate $\gamma_{bd}(a)$ and experiences a capital gain of $\max\{V_{ho}(a) - p(a) - S_{hn}, 0\}$ and $\max\{V_{ho}(a) - p_A(a) - S_{hn}, 0\}$, respectively. This leads to: $\rho S_{hn} = -c_s + \lambda(V_{ln} - S_{hn}) + \int \gamma_b(a) \max\{V_{ho}(a) - p(a) - S_{hn}, 0\}da + \int \gamma_{bd}(a) \max\{V_{ho}(a) - p_A(a) - S_{hn}, 0\}da$.

Similarly to type-ln individuals without token ownership, low-valuation individuals who neither hold a token nor are actively trying to purchase one in the market have zero utility: $\rho U_{ln} = 0$. Low-valuation individuals who do not hold a token but are actively looking to purchase one in the market pay the deterministic search cost c_s. Like the high-valuation non-holders, the low-valuation individual takes the expectations over all platform sizes. She meets a selling individual at rate $\gamma_b(a)$ and a selling intermediary at rate $\gamma_{bd}(a)$ and experiences a capital gain of $\max\{V_{lo}(a) - p(a) - S_{ln}, 0\}$ and $\max\{V_{lo}(a) - p_A(a) - S_{ln}, 0\}$, respectively. This yields: $\rho S_{ln} = -c_s + \int \gamma_b(a) \max\{V_{lo}(a) - p(a) - S_{ln}, 0\}da + \int \gamma_{bd}(a) \max\{V_{lo}(a) - p_A(a) - S_{ln}, 0\}da$.

6.2.2 *Intermediaries*

Because intermediaries do not enjoy flow utility from holding tokens, there are only two types: intermediaries that currently hold tokens and those that currently do not hold tokens. A platform-size-a token-holding intermediary pays the flow operating cost k, and decides between selling the token for ask price $p_A(a)$ and realizing capital gain $p_A(a) + J_{dn} - J_{do}(a)$ net of any network-related effects on capital or realizing the salvage value (e.g., return tokens in case a hard-cap goal was not met in the offering). The token-holding intermediary's value function satisfies the following Bellman equation: $\rho J_{do}(a) = \max\{-k + \alpha_{ds}\big(p_A(a) + J_{dn} - J_{do}(a)\big) + J'_{do}(a), \rho J_{dn}\big\}$. In contrast, the value function of the token-nonholding intermediary is characterized by the flow operating cost k that the intermediary incurs while actively searching for a potential transaction and the expectation over the platform sizes when the intermediary meets a seller at rate $\alpha_{db}(a)$ and realizes a capital gain in the amount of $max\{J_{do}(a) - p_B(a) - J_dn, 0\}$. It satisfies: $\rho J_{dn} = -k + \int \alpha_{db}(a) \max\{J_{do}(a) - p_B(a) - J_{dn}, 0\}da$. Note that the free-entry condition implies that intermediaries' expected capital gains is exactly offset by their operating cost in the latter equation.

6.3 Prices

Following the literature (e.g., Gavazza, 2016; Weill, 2020), we solve for the endogenous price in the non-intermediated ICO market segment via generalized Nash bargaining: $\max_{p(a)}[U_{ho}(a) - p(a) - S_{hn}]^{1-\theta_s}[p(a) + V_{ln} - S_{lo}(a)]^{\theta_s}$ subject to $U_{ho}(a) - p(a) - S_{hn} \geq 0$ and $p(a) + V_{ln} - S_{lo}(a) \geq 0$. This yields the endogenous price: $p(a) = (1-\theta_s)\big(S_{lo}(a) - V_{ln}\big) + \theta_s\big(U_{ho}(a) - S_{hn}\big)$. The ask price $p_A(a)$ and bid price $p_B(a)$ are determined in a similar fashion: $p_A(a) = (1-\theta_d)\big(J_{do}(a) - J_{dn}\big) + \theta_d\big(U_{ho}(a) - S_{hn}\big)$ and $p_B(a) = (1-\theta_d)\big(J_{do}(a) - J_{dn}\big) + \theta_d\big(S_{lo}(a) - V_{ln}\big)$).

6.4 Policies

6.4.1 Individual investors

Surplus rents from trade arise when hn-type individuals without token ownership meet lo-type token-holders. Those surplus rents from trade are higher for tokens with relatively large underlying platforms due to the negative complementarity between the input factors of flow utility $\pi(z, a)$. By implication, not all tokens are reallocated in equilibrium, which helps simplify the analyses. We can reformulate the value functions of ho-type token-holding individuals. $V_{ho}(a)$ equals $U_{ho}(a)$ for $a < a^*_{ho}$ and S_{hn} for $a \geq a^*_{ho}$. These cases follow from $U'_{ho}(a) < 0$. Because the utility ho-type individuals derive from holding platform-size-a tokens is decreasing in a, there must be a cutoff a^*_{ho} at which token-holders decide to realize the salvage value S_{hn}. Therefore, $U_{ho}(a^*_{ho}) = S_{hn}$. Likewise, such a cutoff also exists for hn-type token-nonholding individuals at which they decide to purchase a platform-size-a token. Therefore, we have $a^*_{hn} \leq a^*_{ho}$, with a potential wedge from trading frictions. Thus, token-nonholding hn-type individuals have the value function $V_{hn} = S_{hn}$. The value function of token-holding lo-type individuals can be simplified as follows: $V_{lo}(a)$ equals $S_{lo}(a)$ for $a < a^*_l$, $U_{lo}(a)$ for $a \leq a^*_l < T$, and V_{ln} for $a = T$. Because $U'_{lo}(a) < 0$ and c_s is constant, there exists a cutoff a^*_l such that a lo-type individual decides to sell her token if it is below the cutoff and keep it if it is above the cutoff, respectively. If she keeps the token, then she holds it until she can realize the salvage value at T. Further, equilibrium considerations dictate that token-holding lo-type individuals sell to purchase-willing hn-type individuals, implying $a^*_l \leq a^*_{hn}$. Finally, because z_l is an absorbing state, the value function of token-nonholding ln-type individuals is $V_{ln} = y$ where y represents the value of the smallest platform.

6.4.2 Intermediaries

Intermediaries prefer tokens with larger underlying platforms because they trade at greater margins, but intermediaries' operating costs k are constant. Therefore, intermediaries purchase platform-size-a tokens such that $a \leq a^*_{dn}$ and realize the salvage value at $a^*_{dn} < a^*_{do}$. Equilibrium considerations also dictate $a^*_{do} \leq a^*_{hn}$, that is, intermediaries always sell to purchase-willing individuals.

6.5 Distributions of individual investors and intermediaries

6.5.1 Laws of motion for individual investors

The mass of platform-size-a token-holding ho-type individuals evolves over time as non-holding hn-type individuals meet selling platform-size-a token-holding individuals $(\gamma_b(a)\mu_{hn})$ or platform-size-a token-holding intermediaries $(\gamma_{bd}(a)\mu_{hn})$, and platform-size-a token-holding individuals switch valuations to the absorbing state z_l $(\lambda\mu_{ho}(a))$; formally: $\dot{\mu}_{ho}(a) = (\gamma_b(a)\mu_{hn} + \gamma_{bd}(a)\mu_{hn}) - \lambda\mu_{ho}(a)$ for $a < a^*_{ho}$. Similarly, the evolution of platform-size-a token-holding lo-type individuals over time is affected by inflows from token-holding individuals with underlying token-platform sizes $a < a^*_{ho}$ (because these individuals would just realize the salvage value if their tokens were based on a smaller platform) whose valuations just switched to the absorbing z_l-state $(\lambda 1(a < a^*_{ho})\mu_{ho}(a))$, and the outflow of lo-type holders of tokens with networks greater than a^*_l (holders of tokens with those platform sizes would prefer to sell rather then keep it) who meet purchase-willing individuals $(\gamma_s 1\big(a < a^*_l\big)\mu_{lo}(a))$ or intermediaries $(\gamma_{sd} 1\big(a < \min\{a^*_l, a^*_{dn}\}\big)\mu_{lo}(a))$. Technically, for low-valuation owners: $\dot{\mu}_{lo}(a) = \lambda 1\big(a < a^*_{ho}\big)\mu_{ho}(a) - \gamma_s 1\big(a < a^*_l\big)\mu_{lo}(a) - \gamma_{sd} 1\big(a < \min\{a^*_l, a^*_{dn}\}\big)\mu_{lo}(a)$ for $a < T$; for high-valuation non-owners: $\dot{\mu}_{hn} = (\mu - x) + \mu_{ho}(a^*_{ho}) - \lambda\mu_{hn} - \mu_{hn}\int_0^{a^*_l} \gamma_b(a)da - \mu_{hn}\int_0^{a^*_{dn}} \gamma_{bd}(a)da$; and for low-valuation non-owners: $\mu_{ln} = \lambda\mu_{hn} + \gamma_s\int_0^{a^*_l} \mu_{lo}(a)da + \gamma_{sd}\int_0^{\min\{a^*_l, a^*_{dn}\}} \mu_{lo}(a)da + \mu_{lo}(T)$.

6.5.2 Laws of motion for intermediaries

Similar logic gives the laws of motion for intermediaries in the model: $\dot{\mu}_{do}(a) = \alpha_{db}(a)1\big(a < a^*_{dn}\big)\mu_{dn} - \alpha_{ds}\mu_{do}(a)$ for $a < a^*_{do}$ and $\dot{\mu}_{dn} = \alpha_{ds}\int_0^{a^*_{do}} \mu_{do}(a)da - \mu_{dn}\int_0^{\min\{a^*_l, a^*_{dn}\}} \alpha_{db}(a)da + \mu_{do}(a^{**}_{dn})$.

7 Structural estimation

This section describes how we estimate and identify the model of the ICO market described in Sect. 6. It also reports key parameter estimates, including search costs, transaction surplus, and rent sharing between individual investors and intermediaries. Finally, we benchmark the ICO market to the perfectly efficient Walrasian equilibrium to quantify the effect of market frictions on aggregate welfare created in the ICO market.

7.1 Estimation

We the model as follows: The discount rate is $\rho = 0.5\%$, the total mass of ICOs is set to equal the sample median, and the average number of active intermediaries, μ_d, is set to the sample mean. ICOs differ in their underlying network size. All ICOs' network sizes are ranked by percentiles from 1 (largest) to 100 (smallest). The unit of time, at which we estimate the model, is set to months, covering 48 months during the 2017–2020 period. The salvage price is $S = \$0$, stipulating that platforms without users are worthless.

Tokenholders' flow payoff equals $\pi(z, a) = ze^{-\delta_2 a}$. We estimate the vector $\psi = \{\lambda, \gamma_s, \gamma_{sd}, \alpha_{ds}, z_h, z_l, \delta_2, c_s, \theta_s, \theta_d\}$. The endogenous contact rates $\{\gamma_s, \gamma_{sd}, \alpha_{ds}\}$ can be inferred from the data and help identify other parameters of the model, which in turn jointly determine individual investor' and intermediaries' policy functions and distributions. The following ICO moments, $m_1(\psi)$, are computed based on the model's solution: (1) The fraction of tokens for sale, $m_1[1] = \frac{\int_0^{a_l^*} \mu_{lo}(a)da + \int_0^{a_{do}^*} \mu_{do}(a)da}{A}$; (2) the cumulative number of intermediated ICOs relative to all ICOs, $m_1[2] = \frac{\int_0^{a_{do}^*} \mu_{do}(a)da}{A}$; (3) the fraction of active non-intermediated ICOs, $m_1[3] = \frac{\gamma_S \int_0^{a_l^*} \mu_{lo}(a)da}{A}$; (4) the fraction of active intermediated ICOs, $m_1[4] = \frac{\alpha_{ds} \int_0^{a_{do}^*} \mu_{do}(a)da}{A}$; and (5) the average ranking of ICO platform's underlying network size, $m_1[5] = \frac{\int_0^{a_l^*} a\mu_{lo}(a)da + \int_0^{a_{do}^*} a\mu_{do}(a)da}{\int_0^{a_l^*} \mu_{lo}(a)da + \int_0^{a_{do}^*} \mu_{do}(a)da}$. Further, six price moments, $m_2(\psi) = \{\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5\}$, are obtained from nonlinear least squares from the following two auxiliary regressions: $p(a) = \beta_0 + \beta_1 e^{-\beta_2 a}$ and $p_B(a) = \beta_3 + \beta_4 e^{-\beta_5 a}$. Then, we estimate ψ via the two-step estimator from Hansen (1982): $\hat{\psi} = \arg\min_{\psi \in \Psi} \big(m(\psi) - m_S\big)' \Omega(\tilde{\psi}) \big(m(\psi) - m_S\big)$ where m_S denotes the simulated token offering and price moments, and $\Omega(\tilde{\psi})$ is the consistent estimate of the asymptotic variance-covariance matrix of the moments, and we use $\frac{m(\psi) - m_S}{m_S}$ to have a similar scale.

7.2 Identification

Identification follows largely the multidisciplinary search literature, including labor (Eckstein & Van den Berg, 2007) and decentralized real asset markets (Gavazza, 2016). ICO moments identify the transition rates between states. The fraction of non-intermediated ICOs identifies the rate at which individuals meet, γ_s, while the fraction of intermediated ICOs identifies intermediaries' contact rates, α_{ds}. The cumulative number of intermediated ICOs identifies the rate at which individuals meet intermediaries, γ_{sd}. Furthermore, the Markov-chain parameter that governs inventors' valuation changes, λ, is identified by the total fraction of active ICOs in any given instant.

The valuation parameter and the endogenous moments together with the fixed parameters A and μ_d and the steady state condition $\frac{\mu}{\lambda} = \mu_{hn} + \int_0^T \mu_{ho}(a)da$ then allow to infer the efficiency parameters of the matching functions, γ and γ', and the mass of new market entrants, μ. Specifically, we solve for $\mu_{ho}(a)$, $\mu_{lo}(a)$, and $\mu_{do}(a)$ in the law-of-motions equations in Sect. 6.5.

To identify the remaining parameters $\{\delta_2, z_h, z_l, \theta_s, \theta_d, c_s\}$, we use the price moments and the fifth transaction moment that characterizes the average platform's underlying network sizes of the marketed ICOs. The price equations identify the value depreciation parameter, δ_2, from price variations across tokens of different underlying network size.

We follow Gavazza (2016) to identify bargaining and valuation parameters who suggests to exploit differences between the prices in intermediated and non-intermediated ICOs, as well as the vertical heterogeneity of the token network sizes. β_0 and β_3 in the price regressions identify hn non-tokenholders' value of continuing to search, S_{hn}, which is their outside option in Nash bargaining with equilibrium prices. Because non-tokenholders do not know the token's underlying network size of the token of the tokenholder they meet next, S_{hn} does not depend on the token's underlying network, and hence the intercepts from the price regressions are sufficient for identification. S_{hn} depends on valuations $\{z_l, z_h\}$ and bargaining parameters $\{\theta_s, \theta_d\}$. S_{hn} is negative if the transaction surplus is exclusively appropriated by selling individual and intermediaries. S_{hn} increases in the combined buying individuals' bargaining power, $(1 - \theta_s) + (1 - \theta_d)$. This also implies that the price regression intercepts identify valuations and bargaining parameters. Tokenholders' flow payoff, $\pi(z, a) = ze^{-\delta_2 a}$, and the negotiated prices imply that β_1 and β_4 also help identify valuations and bargaining parameters.

The average network size of marketed tokens identifies the flow search costs, c_s. Search costs matter for sellers when they face the decision to market the token, however, they do not matter when they meet potential buyers and negotiate, as they are sunk by then. Transaction surplus is larger for low-a ICOs because buyers are able to extract higher rents from network effects. This implies that the average ranking identifies c_s because high-a tokens are only put on the market in the presence of sufficiently low search costs.

Intermediaries' fixed costs, k, are easily identified from their bid-ask spread and their trading rates because we stipulated free market entry for institutional investors.

7.3 Parameter estimates

Parameter estimates are in Table 6. Changes in valuation occur with intensity $\lambda = 0.0624$, suggesting that high-valuation individuals switch to low-valuation investors for a particular platform on average every 16 ($\frac{1}{0.0624}$) months, which seems to be a reasonable estimate in an intermediated ICO market (Fisch & Momtaz, 2020). The contact rates for selling individuals meeting buying individuals and buying intermediaries is $\gamma_s = 0.2169$ and $\gamma_{sd} = 0.2537$, respectively. In contrast, the estimated contact rate for intermediaries, $\alpha_{ds} = 0.7099$, suggests that intermediaries are able to sell tokens significantly faster. Overall, these estimates indicate that search frictions for individuals are sizable in the market for tokens, and that intermediaries are able to reduce such trading delays by 33.7%. This estimate closely corresponds to the reduced-form estimate in Sect. 5.2 that intermediated ICOs help startup firms achieve their crowdfunding goals 25% faster, which is a first reconfirming observation in support of the model's overall fit.

To better understand the estimates, we use these endogenous contact rates to infer individuals (γ) and intermediaries (γ') pairwise contact rates (not tabulated). The results are $\gamma = 0.0009$ and $\gamma' = 0.0030$. Hence, intermediaries' pairwise meeting rate is significantly higher, explaining how intermediaries help reduce frictions associated with trading delays.

The valuation differences between sellers and buyers are large. In particular, the difference in the average type-ho and the average type-lo sellers' ICO valuations is \$0.65 million, with a very low lo-type valuation, which is consistent with the notion that selling individuals have no use for the token's platform. These estimates indicate that gains from trade in the market for tokens are sizable. Again, the large valuation differential lends support to our reduced-form estimates for token valuation in Sect. 5.3, also supporting the model's overall fit.

Compared to the average sell-side token valuation, flow search costs are relatively large. The c_s parameter is \$23,124. Therefore, search costs associated with a completed ICO are on average \$49,137 ($\frac{c_s}{\gamma_s+\gamma_{sd}}$), which represents almost 90% of the seller's value of

Table 6 Model-implied ICO market parameters: search, valuation, and rent sharing

Parameter	Notation	Estimate
Intensity of drops in ICO valuations	λ	0.0624
Contact rates in non-intermediated ICOs	γ_s	0.2169
Contact rates in intermediated ICOs: Individuals meet intermediaries	γ_{sd}	0.2537
Contact rates in intermediated ICOs: Intermediaries meet individuals	α_{ds}	0.7099
Platform size-related depreciation rate of ICO valuation	δ_2	0.0165
Buyer valuation	z_h	7.0442e+5
Seller valuation	z_l	5.4677e+4
Flow search costs	c_s	2.3124e+4
Surplus sharing between buying and selling individuals	θ_s	0.3520
Surplus sharing between individuals and intermediaries	θ_d	0.9452

the tokens. Thus, search costs for sellers appear to be pronounced in the ICO market.

The bargaining parameters, θ_s and θ_d, indicate that rent sharing depends on whether an ICO is non-intermediated or intermediated. Rent sharing in non-intermediated transactions favors the buyer who appropriates roughly two-thirds of the transaction surplus, perhaps indicative of the fact that selling individuals reveal their lo type which hurts bargaining power. In intermediated ICOs, however, intermediaries are able to pocket an even larger share of the transaction surplus. This is consistent with the notion that intermediaries are more experienced and hence sophisticated negotiators than inventors ($\theta_d > \theta_s$) (Green et al., 2007a, b).

Finally, we also use the estimates in Table 6 to compute the costs of market making, which are the intermediaries' fixed costs (k, not tabulated). These costs should be nontrivial because of the free-entry condition. Indeed, we find that they are $2.56 million per year.

Overall, these estimates support the view that market frictions are relatively salient in the ICO market, and that the model seems to describe aggregate ICO market dynamics relatively well.

7.4 Model fit

We now examine the model's overall fit more formally. In particular, we contrast empirical ICO-related quantity moments from the data with simulated moments from the model in Table 7. The simulated transaction moments match those in the data relatively well. The average absolute percentage deviation is 0.6%. This means that the model is very good at predicting aggregate ICO market transactions.

7.5 Aggregate findings: ICO market efficiency

The ultimate goal of the structural estimation is to produce insights into how efficient DeFi markets are in aggregate, with an application to the ICO market. To this end, we estimate the Walrasian market as a benchmark for the actual ICO market. The counterfactual Walrasian ICO market assumes that there are no market frictions and, as a consequence, tokens are only held by the highest-valuation investors. To compute the Walrasian counterfactual, we let the contact rates approach infinity, $\gamma \to \infty$, and stipulate that there are no search costs, $c_s = 0$. Intuitively, in the case of Walrasian efficiency, non-tokenholding type-hn investors immediately transact with tokenholding type-lo investors when they enter the market. That is, in equilibrium, no type-lo investor holds a token and intermediaries have no inventory, that is, $\mu^w_{lo}(a) = \mu^w_{do}(a) = 0$ for any a.

We can now compare the actual estimated market to the Walrasian benchmark. The key findings are in Table 8. Market efficiency in the counterfactual Walrasian ICO market is normalized to 100%. Relative to the Walrasian benchmark, the overall ICO market achieves a market efficiency of about one-fifth. In

Table 7 Model fit: aggregate quantity-related ICO market moments, empirical vs. simulated

Empirical Moment	Empirical Value	Theoretical Moment	Simulated Value
$\mathbb{E}\left(\frac{\text{Active ICOs}}{\text{Cumulative ICOs}}\right)$	0.1507	$\frac{\int_0^{a_l^*} \mu_{lo}(a)da+\int_0^{a_{do}^*} \mu_{do}(a)da}{A}$	0.1497
$\mathbb{E}\left(\frac{\text{Cumulative intermediated ICOs}}{\text{Cumulative ICOs}}\right)$	0.1039	$\frac{\int_0^{a_{do}^*} \mu_{do}(a)da}{A}$	0.1038
$\mathbb{E}\left(\frac{\text{Active non-intermediated ICOs}}{\text{Cumulative ICOs}}\right)$	0.1456	$\frac{\gamma s \int_0^{a_l^*} \mu_{lo}(a)da}{A}$	0.1447
$\mathbb{E}\left(\frac{\text{Active intermediated ICOs}}{\text{Cumulative ICOs}}\right)$	0.0051	$\frac{\alpha_{ds} \int_0^{a_{do}^*} \mu_{do}(a)da}{A}$	0.0050
$\mathbb{E}$ (Platform size, Active ICOs)	50.00	$\frac{\int_0^{a_l^*} a\mu_{lo}(a)da+\int_0^{a_{do}^*} a\mu_{do}(a)da}{\int_0^{a_l^*} \mu_{lo}(a)da+\int_0^{a_{do}^*} \mu_{do}(a)da}$	50.17

Average absolute percentage deviation = 0.6%

Table 8 Model-implied ICO market efficiency

Panel A: Aggregate efficiency — Main model for the entire ICO market	
Estimated aggregate efficiency	17.6%
Panel B: Implied segmental efficiency — Entrepreneurial opportunity	
Bull market	10.6%
Bear market	19.8%
Panel C: Implied segmental efficiency — Entrepreneurial quality	
Above-median team rating	19.0%
Below-median team rating	22.8%
Above-median product rating	19.0%
Below-median product rating	24.9%
Above-median vision rating	19.8%
Below-median vision rating	19.1%
Panel D: Implied segmental efficiency — Entrepreneurial incentivization	
Above-median token retention	18.1%
Below-median token retention	18.0%

robustness tests, these efficiency estimates increase to up to one-third of the Walrasian efficiency if the non-intermediated ICO token discount is estimated based on relative measures (instead of the absolute measure of the funding amount in Table 4), such as the funding amount divided by the hard cap amount or the "money left on the table" in terms of the ICO token price relative to the token price one month after the listing. Therefore, search-related inefficiency causes a substantial welfare loss to ICO market participants. Panel A shows the efficiency estimate for the entire ICO market. Panels B, C, and D show implied efficiency estimates for various segments by proxies for market phases, entrepreneurial quality, and entrepreneurial incentivization, respectively. The implied efficiency estimates suggest that search frictions are more pronounced in bull markets and for ICOs with high-quality teams and products, plausibly reflecting deeper markets during the ICO boom and the difficulty to find strong entrepreneurs and projects (Bellavitis et al., 2020; Hornuf et al., 2021; Momtaz, 2021c). It is difficult to contextualize the efficiency estimate for the ICO market because there are no aggregate efficiency studies on other entrepreneurial finance markets. Nevertheless, compared to the decentralized real asset market study on used business aircraft with an efficiency estimate of four-fifth relative to the Walrasian benchmark by Gavazza (2016), the ICO market is clearly less efficient.

8 Discussion

8.1 Summary of main results

This paper examines the efficiency of the ICO market by testing two overarching hypotheses. The ***Disintermediated Inefficiency Hypothesis*** (***DIH***) posits that the ICO market is relatively inefficient because of search-related frictions, while the ***Intermediated Efficiency Hypothesis*** (***IEH***) suggests that new DeFi intermediaries, especially crypto funds, help partially restore the market's efficiency. ICOs are the largest DeFi market segment for startups (Bellavitis et al., 2021), and are particularly interesting because, despite DLT's ability to create perfectly decentralized markets, a growing number of crypto funds are entering the ICO market and reintroducing a substantial degree of intermediation. This development fuels the conjecture that DeFi is relatively inefficient and intermediation is inevitable in nascent markets with highly asymmetric information (Zetzsche et al., 2020). Indeed, reduced-form instrumental variable analyses suggest that search frictions are pronounced in non-intermediated ICOs, and crypto funds help reduce these frictions and extract economic rents for this service. Specifically, intermediated ICOs are able to achieve their crowdfunding goals 25% faster than non-intermediated ICOs, and crypto funds may charge a discount of up to 57% on token value for their intermediation services. Furthermore, we propose and structurally estimate a simple model of the ICO market. The evidence implied by the model suggests that, relative to a perfectly efficient market (the "Walrasian equilibrium"), the ICO market is about one-fifth efficient, with search-related costs accounting for the substantial welfare loss. Intermediaries are well aware of their salient function and appropriate most of the transaction surplus in intermediated ICOs. Overall, both reduced-form evidence and structural estimation support the ***DIH*** and ***IEH***.

8.2 Theoretical contributions and practical implications

This study contributes to the growing literature on the ICO market, as well as to the nascent literature on crypto funds. The first contribution pertains to the market design of DeFi markets for startups. While a growing literature examines startup firm-level determinants of ICO success (e.g., Adhami et al., 2018; An et al., 2019; Belitski and Boreiko, 2021; Bellavitis et al., 2020; Bellavitis et al., 2021; Benedetti and Kostovetsky, 2021; Campino et al., 2021, 2022; Fisch, 2019; Fisch and Momtaz, 2020; Giudici and Adhami, 2019; Hornuf et al., 2021; Huang et al., 2020; Colombo et al., 2021; Momtaz, 2021a, 2021c) the present study shows that ICOs may not be perfectly efficient for reasons that startups cannot directly influence, and that are rather systematically grounded in the ICO market's microstructure. With the results indicating that the ICO market realizes only a small fraction of its welfare potential due to search-related market frictions, the study contributes to several strands in the entrepreneurial finance literature that build implicitly on search. One example is the growing literature on signaling in ICOs (e.g., An et al., 2019; Belitski and Boreiko, 2021; Bellavitis et al., 2020; Campino et al., 2021; Fisch, 2019; Giudici and Adhami, 2019; Lee et al., 2022) as well as adjacent arguments, such as moral hazard in signaling (e.g., Momtaz, 2021c), fraud (Hornuf et al., 2021), or democratization, inclusivity, and literacy in digital finance (Butticé & Vismara, 2022; Fisch et al., 2022; Meoli et al., 2022; Rawhouser et al., 2023). These studies implicitly assume that search frictions are an important reason as to why signaling is a key ICO success determinant, but they never make search frictions explicit. Overall, this paper builds on these prior works, and estimates the aggregate efficiency of an entrepreneurial finance market, as well as the efficiency loss attributable to search-related market frictions.

A second contribution pertains to the very nascent literature on DeFi intermediation through crypto funds. There are now more than 800 crypto funds active, with aggregate assets under management of around $60 billion.[13] Crypto funds may increase the efficiency of startup markets, inter alia, by introducing sophisticated trading strategies to otherwise illiquid entrepreneurial finance markets and through economies of scale associated with search-related human capital investments (Mokhtarian & Lindgren, 2018). Yet, this new intermediary is relatively understudied. Fisch and Momtaz (2020) find that institutional investors' involvement in token offerings certifies a startup's quality and thus increase token valuation and post-offering performance. Cumming et al. (2023) examines a novel dataset with monthly performance data for crypto funds, and finds that they outperform the market and perform some risk management function for their investors when token markets experience a downturn. A theoretical paper by Wang et al. (2022) establishes that crypto funds may increase token value and that they are able to identify high-quality startups and transact privately. To our knowledge, we are the first to examine how crypto funds impact search frictions, equilibrium asset allocations and prices, and welfare overall. In particular, this study contributes to the emerging literature on DeFi intermediation (for seminal arguments, see Boreiko and Vidusso (2019), Schueffel (2021), though on the different intermediation channel of ICO aggregator platforms) by showing that crypto funds improve ICO market efficiency by reducing delays in achieving crowdfunding goals, and plausibly reducing overinvestment in adversely selected low-quality projects as well as underinvestment by asymmetrically informed investors in high-quality projects.

The study has important practical implications for entrepreneurs, investors, and policymakers. Entrepreneurs face a difficult trade-off when choosing between intermediated and non-intermediated ICOs. Intermediated ICOs improve the crowdfunding outcome, but they also impose significant costs associated, inter alia, with unfavorable rent sharing with intermediaries. At the margins, entrepreneurs with a relatively

[13] See https://cryptofundresearch.com/q1-2021-crypto-fund-report/.

large platform user base are likely better off with non-intermediated ICOs, while entrepreneurs with smaller platform user base will benefit from ICO intermediation. For individual investors, their search abilities will determine whether they should invest in intermediated or non-intermediated ICOs. DeFi intermediaries, specifically crypto funds, profit from favorable rent sharing. Given that the DeFi revolution arguably reallocates centralization in financial markets to other parts of the value chain (Zetzsche et al., 2020), the most successful DeFi intermediaries will play important roles in the future of entrepreneurial finance. The implications for policymakers are intricate. While DeFi intermediaries remedy several structural problems in the ICO market, such as manifestations of moral hazard (Momtaz, 2021c) or fraud Hornuf et al. (2021), they may create a number of new problems. In particular, crypto funds trade in tokens, which are classified as "non-securities" (Mokhtarian & Lindgren, 2018), which, in turn, exempt crypto funds from most financial market regulations. This enables new trading strategies in entrepreneurial finance markets, such as short selling, with possibly highly detrimental consequences for tokenized startup firms. As such, more work is required to understand how new entrepreneurial finance markets may benefit from regulation, auditors, and arbitrageurs. Importantly, ICOs now co-exist with similar token-based crowdfunding mechanisms, such as Initial Exchange Offerings (IEOs) and Non-Fungible Tokens (NFTs). The results reported in this study plausibly extend to these markets, with the particularities that IEs likely exhibit less and NFTs exhibit more search frictions.

8.3 Limitations and avenues for future research

This study represents an initial step toward quantifying the aggregate efficiency of DeFi markets for startups, with a focus on how market frictions impact token allocations, prices, and overall welfare in ICOs. Given the soaring interest among entrepreneurs and investors in various DeFi markets that extend beyond the ICO market, as well as the growing body of research (for excellent reviews, see Brochado and Troilo, 2021; Kher et al., 2021), it is likely that a broad research program will evolve around these themes. Below, we suggest potential avenues for future research.

Sources of welfare losses This study has quantified the aggregate efficiency of the ICO market, and finds that market frictions reduce the realized welfare by 48% relative to the Walrasian equilibrium. However, the study does not disentangle the precise sources of the efficiency losses. Several related studies show that frictions include, inter alia, adverse selection or outright fraud (Hornuf et al., 2021), poor governance (Giudici et al., 2020), moral hazard (Momtaz, 2021c), geographic frictions (Huang et al., 2020), and regulatory frictions (Bellavitis et al., 2021). Yet, the relative importance of these frictions for welfare losses in the ICO market is not clear, which prevents targeted policy interventions. Similarly, there is little evidence as to the types of frictions that entrepreneurs can mitigate themselves, e.g., via signaling (Fisch, 2019), vis-à-vis frictions that need to be addressed systematically by regulators and policymakers (Zetzsche et al., 2020). Therefore, a potentially fruitful avenue for future research involves evaluations of policy interventions in the ICO market (for an overview, see Bellavitis et al., 2021), and their impact on entrepreneurs and aggregate market efficiency.

Heterogeneity across entrepreneurs, investors, and intermediaries DeFi market frictions and efficiency are largely unobservable, which is the reason why we have to rely on a model. Every model necessarily abstracts from reality and makes simplifying assumptions to be analytically tractable or facilitate structural estimation. For example, the present model assumes that there are only two types of tokenholders that purchase tokens from entrepreneurs: individual investors and intermediaries. Yet, these two investor categories are heterogeneous. For instance, crypto funds employ different investment strategies, ranging from venture-style funds to quantitative hedge funds. How these strategies influence their role as intermediaries is unexplored in this paper, but seems interesting for future research. Similarly, there are various types of intermediation, e.g., platforms that promote ICOs (Boreiko & Vidusso, 2019), exchanges that conduct Initial Exchange Offerings (IEOs), VCs that invest in equity-token bundles (Fisch & Momtaz, 2020), and many others. Similarly, not only investors and intermediaries, but also entrepreneurs, are heterogeneous. Our model regards entrepreneurs as such with respect to their platform's underlying user base. However, Fisch (2019), Adhami et al. (2018), Bellavitis et al. (2021), Huang et al. (2020), Mansouri and Momtaz (2022), and Momtaz (2020b), among many others, report that token-issuing startup firms differ substantially in terms of their size, human capital stock, and business model. Therefore, it seems interesting to further investigate the startup firm characteristics that make intermediation more or less attractive for entrepreneurs.

Comparisons across crowdfunding models There is relatively little comparative work on the aggregate efficiency of the various crowdfunding markets. However, crowdfunding markets are inherently different; while many market design problems are shared among crowdfunding markets (e.g., the inherent problem of fraud, see Hornuf et al., 2021; Cumming et al., 2021), other institutional features, such as investor motivations (Fisch et al., 2021) and the market-microstructure (Cumming & Vismara, 2017), are dramatically different. For example, in the ICO context, token-based crowdfunding improves upon other crowdfunding models with regard to transactional efficiency thanks to DLT, whereas the increased granularity of token-based crowdfunding markets due in large part to fractional ownership and lower entry barriers may put the ICO market at a relative disadvantage in terms of search-related efficiency. Of course, our structural estimation builds on the specific sample and the design of our reduced-form analyses; changes in the sample or the regressions might alter the estimated parameters in the theoretical model. Similarly, among DeFi market segments, search frictions vary in their types and intensities. For example, for blockchain-based collateralized lending, the ramifications of search are arguably less salient because of the constrained downside risk thanks to the collateral. These comparative trade-offs lead to the fundamental question of the "socially optimal" crowdfunding model, that is, whether there is a single crowdfunding market that is superior to others in terms of the welfare it creates for society.

9 Conclusion

This paper has shown that Decentralized Finance (DeFi) markets for startups, in particular the Initial Coin Offering (ICO) market, can be relatively inefficient. Relative to the Walrasian equilibrium, in which only the highest-value investors purchase tokens at fair prices from entrepreneurs in frictionless markets, the ICO market is significantly less efficient due to pronounced search frictions. As such, this paper provides an explanation for the emergence of DeFi intermediaries, in particular crypto funds, that are able to reduce search frictions and extract substantial economic rents for this service. Overall, without an efficient matching mechanism for entrepreneurs and investors, the results suggest that perfectly disintermediated entrepreneurial finance markets are inefficient and a certain degree of intermediation is likely to persist.

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