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The Wisdom of Crowds in FinTech: Evidence from Initial Coin Offerings

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Certification by analysts on a FinTech platform that harnesses the "wisdom of crowds" is associated with successful initial coin offerings (ICOs). We show that favorable ratings by a group of analysts with diverse backgrounds positively predict fundraising success and long-run token performance. Analysts' ratings also help detect potential fraud ex ante. We document that analysts have career concerns and are incentivized by the platform to issue informative ratings. Overall, our results suggest that a market-based certification process that relies on a diverse group of individuals is at play in financing blockchain startups. (*JEL* D82, G11, G24, G32, G34, L26).

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In recent years, initial coin offerings (ICOs) have emerged as a new form of crowdfunding for blockchain-related startups. In an ICO, an entrepreneur raises capital by creating and selling a virtual currency or "token," which provides a set of rights to its holders, including access to a platform, and can be resold in secondary markets. However, a high degree of information asymmetry associated with the young startups is exacerbated by the lack of a traditional underwriting process that initial public offerings (IPOs) employ, which could hinder successful fundraising.

In this study, we examine whether the "wisdom of crowds," the collective opinion of a group of individuals rather than that of a single expert, can mitigate information asymmetry associated with ICOs. Specifically, the wisdom of crowds refers to an ICO's aggregated rating or "headline" rating, a weighted average of ratings by analysts active on a prominent rating platform. Our setting is unique in that the online platform facilitates active participation by a group of analysts, which is an essential element to form what Surowiecki (2005) terms a "wise crowd." This wisdom of crowds phenomenon is increasingly common among FinTech platforms and our findings therefore have broad implications beyond the ICO market. For example, many blockchain-based prediction market platforms, such as Augur, are designed to harness the wisdom of participants who speculate on a variety of real-world events to produce optimal forecasts.

We hypothesize that this market-based certification mechanism helps screen out "lemons" (Akerlof, 1970) in the ICO market. While the diverse opinions of multiple analysts could produce an aggregate signal that reflects the quality of a risky startup, it is not a priori clear whether the wisdom of crowds applies in the ICO context. Unlike traditional equity analysts at investment banks, ICO analysts do not receive any direct compensation for their ratings and thus may not have an incentive to issue accurate ratings. ICO analysts are also less likely to have a finance or business background. Rather, they have diverse backgrounds, such as information technology and data science. Thus, whether these analysts fully understand the financial transactions involved in an ICO is unclear. Despite these institutional differences, we find strong evidence that the aggregate rating from these analysts is informative about whether an ICO is a good investment opportunity.

Our analysis builds on a comprehensive sample of 3,392 completed ICOs for the period running from January 2016 through December 2018. We gather key ICO characteristics from ICObench.com, a popular online platform that maintains a comprehensive database on ICOs. One main distinction between ICObench and other ICO-related platforms (e.g., TokenData.io and ICORating.com) is that the former hosts an active base of online analysts, which provides an ideal environment to study the wisdom of crowds phenomenon. We supplement those data with the information that we manually collect from other publicly available sources when ICObench data are incomplete or missing. We further collect from ICObench individual analyst's ratings. This information enables us to examine whether and how analysts' ratings predict the likelihood of fundraising success in which an ICO reaches its minimum fundraising target ("soft cap") as well as long-term token performance. To further shed light on fraudulent behavior involving token sales, we collect information on ICOs that were subsequently accused of fraud by U.S. regulators. Our study is also unique in its reliance on primary market token subscription information *during* the fundraising period, which allows us, for the first time in the literature, to study how investors purchase tokens during the early stages of a token sale.[1]

First, we find that the probability of a successful fundraising campaign increases by 14.4 percentage points (relative to the unconditional success probability of 42.4%) given a one-standard-deviation increase in the headline rating when controlling for various ICO characteristics. Given that the information sources (e.g., white papers) that ICO analysts rely on are largely nonfinancial and technical, our result suggests that, on average, ICO analysts are able to process complex qualitative information as opposed to quantitative financial information (Bradshaw, 2011).[2] These results support the notion that these analysts can provide positive information intermediation to the ICO market, which lacks traditional underwriters.

To shed light on the notion of the wisdom of crowds, we show that the greater the number of analysts covering an ICO, the more informative the headline rating. This is because when more individual analyst's ratings are aggregated, noises in ratings are more likely to cancel each other. Furthermore, using hand-collected information on analysts' educational backgrounds, we find that a headline rating formed by a more diverse group of analysts is more informative in predicting fundraising success. The results are consistent with Surowiecki (2005), who emphasizes that diversity of opinions makes the aggregate signal more informative.

We provide supportive evidence on the potential channels by which ratings affect fundraising success. Using unique token subscription data collected from Etherscan, a leading "block explorer" that provides information on token transactions, we find that favorable headline ratings

[1] While a recent study by Howell, Niessner, and Yermack (2020) focuses on token liquidity as one of the factors contributing to ICO outcomes, our paper emphasizes a market-based certification mechanism that involves online analysts. We use unique data on ICO analysts, fraudulent ICOs, and token subscription details from the Ethereum blockchain. Among contemporaneous work on ICOs, ours is the first study to include a comprehensive analysis of these novel data.

[2] See Bradshaw (2011) for a review of papers on how analysts use quantitative information to produce earnings forecasts and stock recommendations.

spur aggressive early token subscriptions by outside investors. In addition, we find suggestive evidence that participants in a popular message board featuring cryptocurrencies and ICOs, BitcoinTalk.org, also pay close attention to analysts' ratings.

Importantly, we examine whether ratings are useful in predicting token performance beyond the fundraising stage. This long-run analysis helps us rule out any self-fulfilling equilibrium, in which analysts issue favorable ratings and outside investors blindly follow their opinions. We document that headline ratings successfully detect potentially fraudulent ICOs, which are typically charged by regulators after token sales end. We also show that ratings predict long-run token performance in the secondary market and are associated with lower token price volatility. Higher ratings also predict a lower probability of being delisted by major exchanges over various horizons.

Next, we attempt to understand why analysts devote their time and effort to issuing informative ratings. We test whether career concerns play a key role in incentivizing online analysts to issue more informative ratings. Although analysts do not obtain direct financial rewards for their ratings services (i.e., analysts do not receive any portion of the gross proceeds raised by the ICO they rate), reputable analysts receive indirect compensation in the form of obtaining advisory positions associated with future ICOs.[3] This implicit career incentive can potentially discourage analysts from issuing favorable ratings regardless of ICO quality.[4]

We find that the number of ICOs an analyst has covered is associated with a significant increase in the probability that the analyst holds advisory positions in the subsequent 3 to 6 months. ICObench uses the number of ICOs covered as one major factor to determine an analyst's track record. We further find that being a "top-10 expert," a designation based on analysts' track records, is also related to a 32.9- to 45.1-percentage-point increase in the probability of holding advisory positions. These results suggest that future advisory roles potentially incentivize analysts to acquire and process valuable qualitative information from ICO white papers and other sources.

In the remainder of our paper, we further study how a unique feature of ICObench's platform design can encourage analysts to produce informative ratings. When ICObench generates a headline rating, it weights the ratings from analysts who cover the same IPO. Analysts with good track records of producing high-quality ratings attain a greater weight in the aggregate. Moreover, the rating with the highest weight is featured at

[3] See Section 6.1 for details on analysts' compensation.

[4] Nevertheless, we acknowledge that during a market downturn, such reputation-based incentives would become weaker, increasing the likelihood that some analyst would offer rosy ratings on request as a result of lower expected reputational value.

the top of each ICO's ratings section, giving the top-ranked analysts more visibility. For the subset of analysts who simultaneously cover multiple ICOs, we identify the ICO that gives each analyst the most visibility in the ICO community. This identification strategy builds on the *relative* importance of an ICO to an analyst, who would spend greater effort and time on the ICO that maximizes her visibility in the ICO market.

An analyst's relative rank in a given ICO is determined not only by the analyst's own track records but also by other analysts' records and is therefore difficult to manipulate systematically. Using this quasi-exogenous within-ICO rank of an analyst, we examine how visibility affects the analyst's incentive to exert effort. Given that an analyst would revise her rating when her previous rating no longer well represents the quality of an ICO and that a revision often entails expending additional time and resources, a revision proxies for effort in issuing ratings. When controlling for analyst fixed effects, we find that an individual analyst is more likely to revise her rating if the covered ICO gives her the highest visibility and the rating becomes more informative in predicting fundraising success. These analyst-level analyses also help mitigate endogeneity concerns due to potential ICO-level omitted factors that are correlated with fundraising success.[5] Overall, our results suggest that more powerful reputational incentives induce analysts to exert more effort and produce more informative ratings.

We make several contributions to the growing literature on ICOs.[6] First, we relate our findings to recent theoretical papers on ICOs, which include Cong, Li, and Wang (2021), Gan, Tsoukalas, and Netessine (2021), Lee and Parlour (2021), Li and Mann (2020), and Sockin and Xiong (2020). For example, our analysis of post-ICO token performance is related to Cong, Li, and Wang (2021), who develop a dynamic asset pricing model of tokens that features intertemporal feedback effects. Our study is also related to that of Howell, Niessner, and Yermack (2020), who examine which ICO characteristics predict employment and enterprise failure with an emphasis on the effect of token liquidity. We instead

[5] A positive relationship between the headline rating and fundraising success could be attributed to an omitted measure on ICO quality that is observed by both investors and analysts. Unless both groups are completely uninformed, this situation is possible. For a more in-depth discussion on this potential omitted variable problem, see Section 1.1.

[6] A number of recent empirical ICO papers focus on variables such as the amount raised, token underpricing, investor returns, exchange listing, post-ICO liquidity, and GitHub activity. On the amount raised, see, for example, Adhami, Giudici, and Martinazzi (2018), Fenu et al. (2018), Fisch (2019), Momtaz (2020), and Aggarwal, Hanley, and Zhao (2020). On token underpricing, see, for example, Benedetti and Kostovetsky (2021) and Dittmar and Wu (2019). On investor returns, see, for example, Benedetti and Kostovetsky (2021), Dittmar and Wu (2019), Hu, Parlour, and Rajan (2019), and Lu (2018). On exchange listing, see, for example, Amsden and Schweizer (2018), Lyandres, Palazzo, and Rabetti (2020), and Deng, Lee, and Zhong (2018). On liquidity, see, for example, Howell, Niessner, and Yermack (2020) and Lyandres, Palazzo, and Rabetti (2020). On GitHub activity, see Howell, Niessner, and Yermack (2020) and Deng, Lee, and Zhong (2018). See Li and Mann (2019) and Ofir and Sadeh (forthcoming) for a review of the recent empirical studies on ICOs.

focus on the role of a diverse group of analysts, and find evidence consistent with the premise that their ratings help mitigate information asymmetry in a market without traditional underwriters. Our paper also complements the contemporaneous work by Bourveau et al. (2018), who study voluntary disclosure of "hard" information through white papers.

Our study is also related to an emerging body of literature on the wisdom of crowds. Chen et al. (2014) show that investor opinions transmitted through social media platforms predict future stock returns and earnings surprises. Da and Huang (2020) study earnings forecast consensuses from a crowdsourcing corporate earnings forecast platform and find that the more public information users view, the more they underweight their private information. One major difference of our setting is that information asymmetry associated with ICO startups, which are typically young blockchain enterprises,[7] is likely much higher than that in listed stocks. Other theoretical studies in this area include Surowiecki (2005), Kovbasyuk (2011), Kremer, Mansour, and Perry (2014), Dindo and Massari (2017), and Li (2018a).

Finally, our findings contribute to the ongoing discussion of ways to improve the design of cryptocurrency crowdfunding platforms. After experiencing a rapid rise in 2017-2018, the ICO market began to cool in late 2018, a development that was likely attributable to regulatory uncertainty and adverse cryptocurrency market conditions.[8] Responding to regulatory concerns that some issued tokens may be deemed securities, a growing number of startups have structured their ICOs as security token offerings (STOs). Initial exchange offerings (IEOs), in which token sales are administered by cryptocurrency exchanges that serve as an additional layer of intermediation, have also emerged as an alternative fundraising option.[9] Analysts continue to cover these alternative token sale methods. Understanding the role of ICO analysts over the boom and bust cycle is, therefore, useful for designing crowdfunding platforms that strive to achieve a higher level of informational efficiency.

7 Another related area is the burgeoning literature on the economics of blockchain technology. Harvey (2016) discusses the mechanics of cryptofinance as well as applications of crytofinance, including Bitcoin. Yermack (2017) considers how blockchain technology can lead to changes in corporate governance. Cong and He (2019) show that blockchain-based decentralization can mitigate information asymmetry and improve welfare. Saleh (2021) provides a formal economic model of the proof-of-stake blockchain protocol. For a broad overview of these recent developments in blockchain economics, see Allen, Gu, and Jagtiani (2020).

8 A surge in cryptocurrency prices since the COVID-19 pandemic appears to have revived the ICO market, according to the ICO calendar from CoinMarketCap.com, which is accessible through https://coinmarketcap.com/ico-calendar.

9 See Appendixes A and B for additional details on the regulatory environment and the evolution of token sales.

1. Conceptual Framework

In this section, we introduce a conceptual framework that explains the meaning of "wisdom of crowds," the role of analysts in the opaque and potentially fraudulent environment of ICOs, and the implication of the wisdom of crowds in the ICO setting, which we cannot fathom from a parallel yet drastically different IPO environment.

1.1 The wisdom of crowds in ICOs

Conventionally, "wisdom of crowds" is defined as the collective opinion of a group of individuals rather than the advice of a single expert. The literature has generally applied this concept to study whether information aggregation across a *diverse* population of agents leads to better decisions (Surowiecki 2005).

In our context, the wisdom of crowds refers to an ICO's aggregated rating or *headline* rating, a weighted average of ratings by analysts active on ICObench, a prominent rating platform. One testable implication of this notion is that the headline rating should inform whether an ICO is a good investment opportunity. That is, there exists a positive relationship between the headline rating and proxies for ICO performance, including fundraising success and long-term token performance.[10] Furthermore, the more diverse the analyst group, the more informative the headline rating. This is because information aggregation across a diverse group of analysts is more likely to cancel out noises in individual ratings.

In our setting, the crowd consists of a group of analysts with diverse backgrounds, 43% of whom have some science/technology training. We argue that the presence of analysts with science/technology backgrounds increase diversity, compared to groups in which everyone is technically unsophisticated, and that substantial heterogeneity exists within this subset of analysts. Some have degrees in computer science, while others have been trained in science/engineering fields. However, few analysts have any formal training in blockchain-related fields, precisely because the subject is so new. We emphasize that analysts with science/technology backgrounds may not necessarily be experts but are likely to offer some unique and diverse insights on the technical aspects of ICOs.

Our notion of the wisdom of crowds is consistent with the existing literature on crowd-sourced analysts. For example, Da and Huang (2020)

[10] The long-run analysis helps rule out any self-fulfilling equilibrium, in which analysts issue favorable ratings and outside investors blindly follow their opinions. Nevertheless, investors could have opinions similar to those of analysts and make investment decisions without referring to analysts' ratings. This could lead to the same positive association observed unless analysts and investors are completely uninformed. Our evidence that potential investors on BitcoinTalk.org pay close attention to ratings helps mitigate this concern. Moreover, while not conclusive, some evidence in the literature supports the view that retail investors in the cryptocurrency market are not sophisticated. For example, Ahn and Kim (2020) extract investor sentiment on Bitcoin from BitcoinTalk.org and do not find any relationship between retail investor sentiment and future Bitcoin returns. Canbaz (2020) shows similar findings.

study the wisdom of 2,516 users on Estimize.com, with one-third being financial analysts coming from buy-side, sell-side, or independent research firms. The remaining users include working professionals from different industries and students. Da and Huang (2020) show that this diverse group's opinions accurately predict future stock earnings.

1.2 The role of analysts in the ICO market

Holmstrom and Tirole (1997) argue that an intermediary that exerts unobservable effort in certifying a borrower must have the incentive to exert such effort. For example, holding capital in the borrower's project can incentivize a bank. Unlike a bank, however, a third-party rating agency does not hold any capital in the firm it certifies. Rather, it relies on reputation alone when providing certification services, which is also the case for ICO analysts. A key question we ask is whether a third-party analyst improves the allocation of capital in the token economy without holding a direct stake in the company it certifies.

Unlike rating agencies that receive direct compensation from issuers, which can lead to ratings shopping and hence ratings inflation (Bolton, Freixas, and Shapiro, 2012), analysts on the ICObench platform do not have such conflicts of interest. Instead, reputable analysts receive indirect compensation from advisory positions associated with future ICOs. Analysts, however, do not receive any portion of the gross proceeds raised by the ICO they rate.

However, we note that conflicts of interest could arise when an ICO entrepreneur privately offers analysts direct payments in exchange for high ratings. This is analogous to the conflict of interest that proxy advisory firms face when they obtain consulting fees from corporations in addition to voting services (Li, 2018b). We argue that during boom times, this is less of a concern because the expected value from maintaining a good reputation likely exceeds a "side payment." However, during the downturn that started in July 2018 (near the end of our sample period), some analysts might be willing to offer rosy ratings upon request as a result of lower expected reputational value.

While this is a reasonable hypothesis, ICObench employs a platform-based incentive scheme to mitigate this concern. Analysts compete to earn high expert scores (up to 100 points) that represent "reputation" on this platform because analysts with high expert scores are more likely to be hired as advisors by entrepreneurs running future ICOs. The expert score is determined by multiple factors, including the accuracy of past ratings. For example, for each ICO that turned out to be a scam, to which an expert gave an average score of 4.0 or more (out of 5.0), 3 to 5 points are deducted from the rating score, which is an important part of the expert score. Therefore, analysts who care about their long-term reputations on the platform are discouraged from issuing favorable ratings regardless of the quality of ICOs, which alleviates potential conflicts of interest.

1.3 Analysts as an integral part of ICOs

We emphasize that despite several similarities between ICOs and traditional IPOs in terms of their processes, several fundamental differences between them exist, including some basic problems. For example, ICOs possess a greater ability to manipulate prices and are far less transparent with respect to the identities of their investors and issuers.[11]

One main difference is that information asymmetry associated with ICOs is typically more severe than that in IPOs. First, cryptocurrency ventures are much younger and less established compared with IPO firms. The latter tend to have tangible assets and developed products for their customers. In contract, most ICOs offer only a blueprint of their future development, which is typically envisioned in white papers posted on the ICO webpages. Such information may not be sufficient for individual investors to understand the underlying venture. Second, most ICO investors are retail investors, who likely lack sufficient knowledge of the underlying project (especially when the project develops innovative technologies) and financial markets in general. In contrast, IPO investors are mostly institutional investors who are generally more sophisticated than ICO investors.

In the absence of a traditional underwriting process, we hypothesize that the wisdom of crowds may work as an alternative, market-based certification mechanism in the ICO market. First, IPO book building is mostly done *offline* by the underwriter (and company management), who visit institutional investors and gauge their demand for the new issue. "ICO book building," however, is mainly conducted *online*, with the help of smart contracts and public blockchains. This "open-source" feature can encourage active participation by analysts with diverse backgrounds, which is an essential element for the wisdom of crowds (Surowiecki, 2005). Second, during IPOs, equity analysts associated with the underwriter are not allowed to participate due to potential conflicts of interest. In contrast, online ICO analysts are most active during the period before the fundraising starts.

Overall, the key differences between ICOs and IPOs echo our main research question: can a third-party analyst improve the allocation of capital in the token economy without holding a direct stake in the company she certifies? Our answer is yes to the extent that reputation incentives are at work and the wisdom of crowds therefore has the potential to

11 Differences in fundraising steps taken by ICOs and IPOs are detailed in Table A1 in the appendix.

assume the role played by intermediaries, such as rating agencies or underwriters, in conventional capital markets.

2. Institutional Background

2.1 The ICO process

An ICO is a new fundraising method made possible by the development of blockchain technology and cryptographic tokens. Through an ICO, a technology startup creates and distributes its (decentralized) platform's digital tokens in exchange for cryptocurrencies, such as Ether (ETH) or Bitcoin (BTC), or fiat currencies, to raise public capital for their operations and product development. The token typically provides a specific set of rights to its holders, including access to a platform or network, rights to create or develop features for an ecosystem, and the right to cast a vote on governance issues, among others.

A typical ICO begins with the presentation of a white paper, which describes the business idea and model, the team, and the technical specifications of the underlying project. The entrepreneurs lay out a timeline for the project and describe how raised funds will be spent, such as on marketing, and research and development. They often specify a "soft cap" that is the minimum amount received at which the initial offering will be considered a success. Startups usually specify a "hard cap" as well, which is the maximum fundraising goal for a crowdsale.

An ICO fixes the number of tokens on offer before the sale. The white paper and/or the project website features a discussion of how the tokens will be distributed, including how many tokens are for sale and how many tokens insiders will keep. Retaining a reasonably high fraction of tokens with the firm can send a signal to the market that the entrepreneurs have more skin in the game, and thus are more likely to expend serious efforts in developing the project (Leland and Pyle, 1977; Downes and Heinkel, 1982).

Investors who purchase tokens early may be given preferential terms, in the form of an "early bird" bonus or discount. One purpose of the bonus or discount is to compensate for the higher risks early buyers bear. Some ICOs include a presale period, also known as a pre-ICO. Presales generally target larger investors, many of whom are institutional investors. The fundraising targets for presales are usually lower than those for the main sales, and tokens are typically sold at steep discounts.

By industry convention, an ICO is considered a success if the amount it collects surpasses the soft cap. If a token sale does not reach its soft cap, funds are usually returned to investors. This is the "all-or-nothing" arrangement commonly used in ICOs. In rare cases, a team may decide to move forward regardless. If the hard cap is reached, additional subscriptions will be rejected and the funds will be returned.

After an ICO is successfully completed, the entrepreneurs typically begin to plan for an exchange listing. Most cryptocurrency exchanges require an application and a listing fee and, depending on each case, the period preceding a listing can last from several days to several months. Secondary market trading starts immediately after listing. If a project is implemented successfully and more capital is needed, a startup may return to the ICO market for a seasoned offering. Figure A1 in the appendix presents the timeline for a typical ICO.

2.2 ICO analysts

In the absence of underwriters, rating platforms are created to assess token sales. ICObench is one of the oldest and most popular platforms on ICOs, and it hosts hundreds of online analysts. Independently, each ICO analyst assigns a rating ranging from 1 to 5 to an ICO for its team, vision, and product-quality assessment. Analysts disclose their real names and biographic information, such as job titles and employers. Analysts consider a team strong and trustworthy if it keeps the community updated with project progress and/or has participated in other cryptocurrency-related projects. Vision mostly concerns what a platform aims to achieve in the mid-term and long-term future. When evaluating products, analysts consider the following aspects: (1) product maturity level—working products are easier to evaluate than concepts, (2) technology, both blockchain- and nonblockchain-related, (3) specific problems with their products/services, (4) a product roadmap that shows short-term and long-term strategies and growth, and (5) projects' commitment to understanding the market environment.

In addition, ICObench provides a rating by an algorithm-based nonhuman analyst (nicknamed the "Benchy" rating) that uses more than 20 distinct criteria. The assessment algorithm divides evaluation into four groups: team, ICO information, product representation, and marketing and social media. Essentially, to produce a rating the nonhuman analyst checks whether any of the above information is available without analyzing it, which is a primary distinction between Benchy ratings and analysts' ratings.[12]

[12] Regarding the team, the algorithm records the number of team members as well as photos, full names, and social media links. A team is considered more trustworthy if any member has participated in multiple ICOs, as either an advisor or a team member. ICO information refers to basic variables, such as token ticker, ICO start and end dates, and soft and hard caps. For product presentation, the algorithm checks the availability of such information through white papers, milestones, and video presentations. The algorithm also monitors activity on various social networks to determine whether an ICO team reaches potential investors.

We use the headline rating, a weighted average of all ratings based on "expert scores."[13] ICObench assigns an expert score to each analyst, which takes into account all the ICOs she has rated. The quality of ratings is a crucial metric for determining each analyst's expert score. ICObench explains that analysts can improve their scores by producing accurate ratings.[14]

3. Sample Description

3.1 The ICO sample

Our sample of ICOs, announced between January 1, 2016, and December 31, 2018, is constructed mainly using ICObench.com. We supplement the ICObench data with data we collect manually from other publicly available data sources when information from ICObench is incomplete or missing. The additional data sources include startups' websites and white papers, popular blogging and social networking sites such as Steemit, Medium, and BitcoinTalk.org, and other ICO data providers such as TokenData.io and ICORating.com.

We collect the following information from the abovementioned data sources: startup name, token ticker, country of incorporation, ICO status (completed, ongoing, or upcoming), start and end dates of an ICO, soft and hard caps, gross proceeds, types of currencies accepted for an ICO, bonus/discount terms, token offer price, the number and percent of tokens for sale, whether an ICO includes a presale, whether a sale has a Know Your Customer (KYC) policy or uses a whitelist, whether an ICO prohibits participation by citizens from certain countries, whether an offering is structured as an STO, startup industry, whether a startup provides information through its website or a white paper in multiple languages, and headline and individual ratings. We select ICOs that were completed by March 31, 2019, with nonmissing key metrics mentioned above. Our main sample includes 3,392 completed ICOs, 811 of which were followed by token listings on cryptocurrency exchanges.

3.2 Secondary market prices, volumes, and transactions

For each of the 811 listed tokens, we collect its daily closing price and trading volume from CoinMarketCap.com, a website that is a top source for pricing data on thousands of cryptocurrencies. For each token, CoinMarketCap aggregates pricing and trading volume information

[13] Interested readers should refer to https://icobench.com/ratings for a more detailed description of ICObench's rating methodology. Details about the expert score can be accessed via https://icobench.com/faq.

[14] ICObench has an incentive to build its reputation as a reliable information provider. As more potential investors refer to it for ICO investment, the platform can earn higher advertisement fees. An example is HitBTC, a major cryptocurrency exchange, advertised on ICObench's home page as of June 2021.

from all major exchanges and produces one standard price quote and trading volume.[15]

3.3 Analysts' backgrounds

Our analyst sample comprises 497 unique analysts. Typically, ICO analysts feature their LinkedIn addresses and Twitter accounts on their ICObench profile pages. If the LinkedIn address is available, we collect the following information: whether an analyst has more than 500 connections, whether an analyst has a science/technology degree, a business/economics degree, or a master's/PhD degree, and whether an analyst received a degree from a *Times* top-100 university. When the Twitter account is listed, we collect the number of years of being active on Twitter, total number of tweets, number of tweets per year, number of followers, and following number. To study analysts' incentives to issue ratings, we further gather career information, including advisory services in future ICOs and whether an analyst is a "top-10 expert," a monthly designation awarded by ICObench based on analysts' track records.

3.4 Primary market subscription data

One unique feature of any token issued through a public blockchain is that each transaction is recorded at every participant's node, and therefore each token subscription during an ICO is publicly available. As 79.2% of our sample projects use the Ethereum platform to run their ICOs, we collect primary market subscription data on all Ethereum-based ICOs from Etherscan, a leading "block explorer" that allows users to search for information about blocks and transactions on the Ethereum Blockchain. Our data include the transaction address, sender address, receiver address, transaction time, and quantity of tokens transferred. We initially identify 2,182 ICOs that have primary market transactions available. In most cases, it is straightforward to identify the insiders as all transfers are originated from one single address. When it is difficult to cleanly identify the insiders, though, we take a conservative approach to exclude from our sample 562 ICOs that involve such identification challenges. We also drop 345 ICOs that distributed tokens *after* the token sales ended. These criteria yield a transactions sample of 1,275 ICOs.

3.5 Potentially fraudulent ICOs

The U.S. Securities and Exchange Commission (SEC), the Commodity Futures Trading Commission (CFTC), and U.S. state securities

[15] To verify whether information from CoinMarketCap is accurate, we also download pricing and volume data from popular alternative pricing sites, such as Onchainfx.com, CryptoCompare.com, and CoinGecko.com. We find that for the vast majority of tokens the prices and volumes from CoinMarketCap are highly correlated with those from the alternative sites (the correlation is typically above 0.9).

regulators have since 2017 prosecuted a number of fraudulent or potentially fraudulent ICOs. Using the Cryptocurrency Litigation Tracker launched by Morrison Cohen LLP, we track SEC, CFTC, and state securities litigation and federal criminal proceedings against cryptocurrency and blockchain entities. After reading court documents for 114 lawsuits filed before March 31, 2019, we determine that regulators accused 48 unique ICOs of fraud.[16] To ensure sample completeness, we conduct an extensive news search in Factiva and obtain nine additional ICOs that were subject to regulatory actions. Of the 57 ICOs subjected to enforcement actions, 41 exist in our sample. Another indicator of potential fraud is whether an ICO's white paper is downloadable. To avoid investor and regulatory scrutiny, scam ICOs often pull their white papers shortly after the sales are concluded, and the associated websites typically go dark as well. Among all 3,392 of the ICOs in our sample, we are not able to download white papers for 262 of them.

It is worth noting that we are the first researchers to utilize information on ICO analysts' backgrounds, investor subscriptions during token sales, and potential fraud in the ICO market.

3.6 Sample overview

Figure 1 plots the quarterly frequency of completed ICOs and the rate of fundraising success during our sample period. As in Mironov and Campbell (2018), we consider a fundraising event successful if its soft cap was reached or the project raised more than $0.5 million in the absence of a soft cap.[17] Just 19 ICOs were completed in 2016. However, the market took off in Q2 2017, with the number of completed ICOs reaching its peak in Q2 2018 before declining during the next two quarters. The fundraising success rate was nearly 90% in the first half of 2017, but then dropped sharply in the second half of the year. The deteriorating success rate potentially reflects the "lemons problem" that lower-quality ICOs were created when the market became red hot (e.g., Akerlof, 1970). The decline in success rates also coincided with increasing regulatory scrutiny worldwide, notably Chinese and South Korean regulators' ban on ICOs in September 2017.

The success rate continued to decline in 2018, approaching 30% in the last quarter of 2018. As shown in Figure 2, the total gross proceeds followed a similar trajectory, topping $2.4 billion in February 2018 before plummeting. The decline in total proceeds appeared to be closely

[16] The remaining 66 cases involved cryptocurrency exchanges or other blockchain-related entities.

[17] In addition to using this industry convention to define ICO success, we also use exchange listing as the criterion for ICO success, as in Amsden and Schweizer (2018) and Momtaz (2020). After a successful fundraiser, startups may take several months to list their token on an exchange. Some entrepreneurs may choose not to list their tokens. In our sample, about 56% of successful fundraising events were followed by token listings as of March 31, 2019.

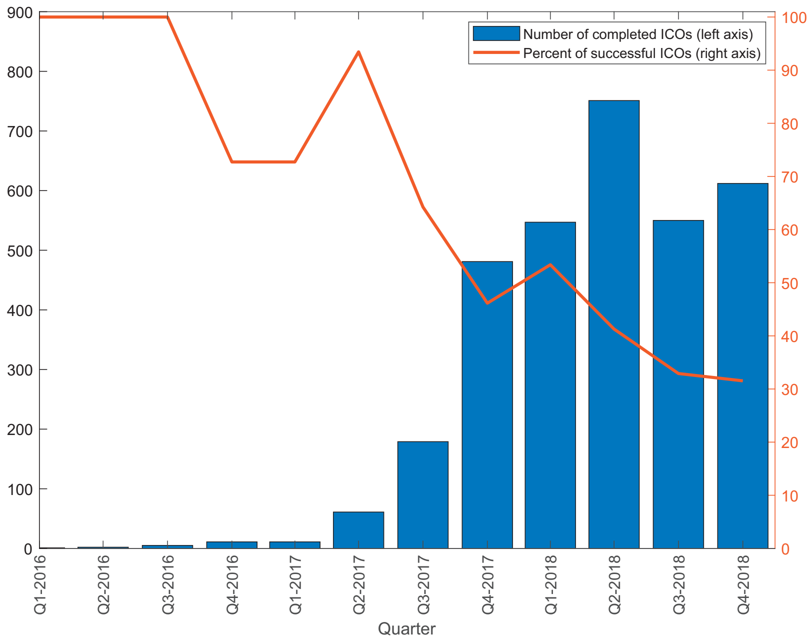

Figure 1
Completed ICOs and fundraising success
This figure features all ICOs that started between January 1, 2016, and December 31, 2018. The blue bars (left axis) plot the number of completed ICOs in each quarter. The red line (right axis) plots the percentage of successful ICOs by quarter. An ICO fundraiser is considered successful if its soft cap was reached or the project raised more than $0.5 million in the absence of a soft cap.

correlated with the decline in the price of Bitcoin (and the prices of other digital currencies). Both the fall in digital currency prices and the impending threat of regulation likely contributed to the cooling of the ICO market.

The top-five largest ICOs to date are EOS, TaTaTu, Dragon Coin, Huobi, and HADC, all of which closed between December 2017 and June 2018.[18] Combined, these token sales raised nearly $5.65 billion, accounting for 46.1% of all ICO proceeds raised during the same period. Table IA1 in the Internet Appendix shows the top-10 largest ICOs as of December 2018, with information on their fundraising periods and gross proceeds. In Table A2 in the appendix, we report the frequency of sales and fundraising success for ICOs from each of the top-10 countries and industries.

[18] We do not count Telegram's $1.7 billion token sale in the first quarter of 2018 because it was structured as a private sale.

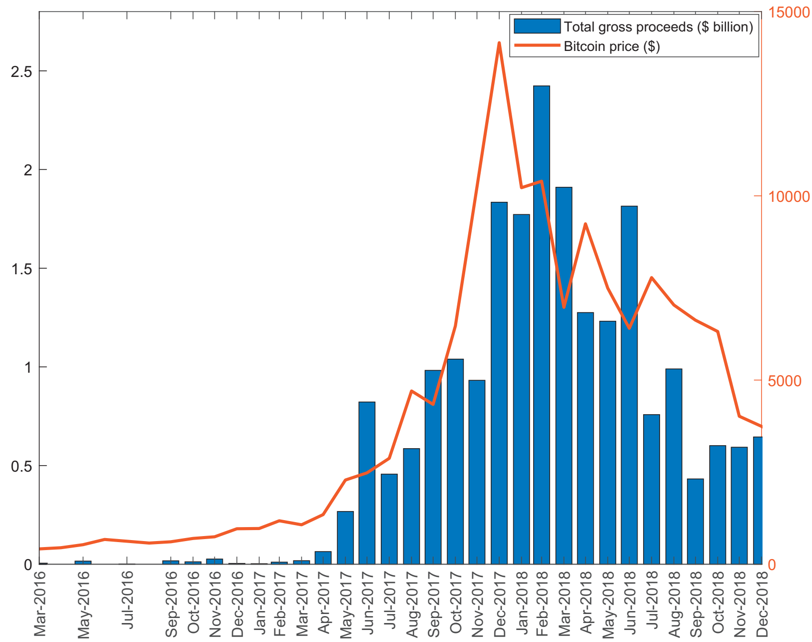

Figure 2
Total gross proceeds and Bitcoin price
In this figure, the blue bars (left axis) plot the total gross proceeds for completed ICOs in each month ($ billion). The red line (right axis) plots Bitcoin's price at the end of each month. Our sample includes all ICOs that started between January 1, 2016, and December 31, 2018. Monthly Bitcoin prices are collected by CoinMarketCap.

3.6.1 Analyst characteristics. Our sample comprises 497 unique ICO analysts. ICObench reports that 260 of these analysts are founders or senior managers from blockchain-related companies, 223 are advisors to these firms, and 112 are blockchain researchers or followers. Some analysts are also investors, with 73 being cryptocurrency/blockchain investors and 22 being venture capitalists or angel investors. Notably, of the nearly 500 analysts, 72 are engineers and/or technicians who are potentially able to provide valuable insights into the technical aspects of ICOs. Other analysts represent a wide range of fields, such as marketing (62), finance/business (59), consulting (48), and law (13), among others. Note that these categories are not mutually exclusive, as a given analyst can play multiple roles.

As shown in Table 1, 93% of our analysts have active LinkedIn pages, and 68.6% of them have active Twitter accounts.[19] All of the analysts

[19] ICObench provides LinkedIn links for 447 analysts and Twitter links for 292 analysts. The LinkedIn and/or Twitter links for three analysts are incorrect, but we are able to obtain the correct links using Google searches. By comparing their profiles and photos on ICObench and those on LinkedIn and

Table 1
Analyst characteristics

	Average	25th percentile	Median	75th percentile	SD	Obs.
Active LinkedIn page	93.0%	100%	100%	100%	25.6%	497
# LinkedIn connections > 500	92.9%	100%	100%	100%	25.8%	462
Science/tech degree	43.3%	0%	0%	100%	49.6%	462
Business/economics degree	47.8%	0%	0%	100%	50.0%	462
Master's/PhD degree	42.4%	0%	0%	100%	49.5%	462
Times top-100 university	19.3%	0%	0%	0%	39.5%	462
No education background	6.5%	0%	0%	0%	24.6%	462
Active Twitter account	68.6%	0%	100%	100%	46.5%	497
# years active on Twitter	6.2	3	7	9	3.5	341
# Tweets	3,786.0	71	483	1,971	15,117.7	341
# Tweets per year	566.0	17.1	101.2	392.4	1,784.1	341
# followers	6,796.0	78	441	1,832	44,723.7	341
# following	3,480.9	74	335	1,225	25,577.6	341
No LinkedIn or Twitter account	3.6%	0%	0%	0%	18.7%	497
# ratings issued	32.0	3	10	33	61.1	497
# ICO advisory positions	2.2	0	0	1	7.3	497
Top-10 expert	6.6%	0%	0%	0%	24.6%	497

In this table, we report characteristics of the 497 online analysts that covered our sample ICOs. *Active LinkedIn page* is an indicator that equals one if an analyst has an active LinkedIn page. *# LinkedIn connections > 500* is a dummy variable that equals one if an analyst has more than 500 connections on LinkedIn. *Science/tech degree* equals one if an analyst holds a university degree in science or technology and zero otherwise. *Business/economics degree* equals one if an analyst holds a university degree in business- or economics-related degree and zero otherwise. *Master's/PhD degree* equals one if an analyst holds a Master's or PhD degree in any discipline and zero otherwise. *Times top-100 university* is an indicator equal to one if an analyst holds a degree from a top-100 university based on the 2019 World University Rankings published by the Times Higher Education. *No education background* equals one if an analyst does not disclose any educational background on their LinkedIn page and zero otherwise. *Active Twitter account* is an indicator that equals one if an analyst has an active Twitter account and zero otherwise. *# years active on Twitter* is the number of years that an analyst has been active on Twitter (as of March 31, 2019). *# Tweets, # Tweets per year, # followers, and # following* are the number of times an analyst tweets, the average number of tweets per year, the number of the analyst's followers, and the number of people the analyst follows, respectively. *No LinkedIn or Twitter account* is a dummy variable that equals to one if an analyst has neither an active LinkedIn nor an active Twitter account and zero otherwise. *# ratings issued* is the number of ratings issued by an analyst. *# ICO advisory positions* is the number of ICOs for which an analyst serves as an advisor. *Top-10 expert* is a dummy variable equal to one if an analyst is ranked among top-10 experts at least once during our sample period and zero otherwise.

who have either a LinkedIn or a Twitter account use their real names. Only one analyst uses two screen names on ICObench, one of which is genuine.

Conditional on having an active LinkedIn page, analysts have more than 500 LinkedIn connections 93% of the time. Nearly 43% of analysts have earned science or technology degrees, while 48% have earned business- or economics-related degrees. This suggests that both science- and business-related degrees are useful to ICO analysts. Perhaps not surprisingly, 42% of our sample analysts hold advanced degrees, and nearly

Twitter, we are able to locate LinkedIn pages for 15 additional analysts and Twitter accounts for 49 additional analysts.

20% of analysts graduated from a global top-100 university, as ranked by the Times Higher Education. Only 6.5% of the analysts do not disclose their educational backgrounds on LinkedIn.

Analysts who own Twitter accounts have been active for 6.2 years on average, with the median being 7 years. The average and median numbers of tweets they send annually are 566 and 101, respectively. On average, they have 6,796 followers. However, the median number of followers is 441, significantly lower than the average. This suggests that a small number of analysts have outsized influence on Twitter.

Only 18, or 3.6%, of all 497 analysts maintain neither a LinkedIn nor a Twitter account. They appear to use their real names as well. We, however, are not able to find their biographic information, other than some news coverage on their ratings and business activities.

The prevalence of social networking by online analysts is important as it brings transparency to the ICO process. As pointed out by Agrawal, Catalini, and Goldfarb (2014), equity crowdfunding investors increasingly use Twitter, LinkedIn, and other social media sites to validate founder profiles when moral hazard is a concern.

On average, an analyst issues 32.0 ICO ratings during our sample period, and serves an advisory role in 2.2 ICOs. In addition, 6.6% of our analysts has won the "top-10 expert" award by ICObench. In sum, we find that the majority of analysts are active on social media, have adequate educational backgrounds, and serve as advisors in other ICOs.

3.6.2 Patterns in primary market subscriptions. To understand the path to fundraising success, we rely on our unique second-by-second subscription data, which are aggregated at various frequencies. Figure 3 plots the time series patterns of daily token sales for both successful and failed ICOs. The blue bars (line) represent daily (cumulative) token sales as a percentage of total token supply for successful ICOs, while the red bars and line represent the corresponding figures for failed sales. In successful ICOs, investors purchase 13.2% of the token supply on the first day, while 30-day cumulative demand is 27.3% of the total supply. In contrast, in failed sales, investors on the first day buy 0.89% of all tokens for sale and cumulative sales are less than 5% of the token supply. This pattern appears to highlight the importance of "winning the battle" during the initial stages of an ICO, which often determines the outcome of the sale. In Internet Appendix Figure IA1, we show similar patterns for hourly and block-level token subscriptions.

3.6.3 Successful fundraisers versus failed ICOs. In Table 2, we report the characteristics of successful fundraising campaigns (columns 1 through 3) as well as their differences with failed ICOs (columns 4

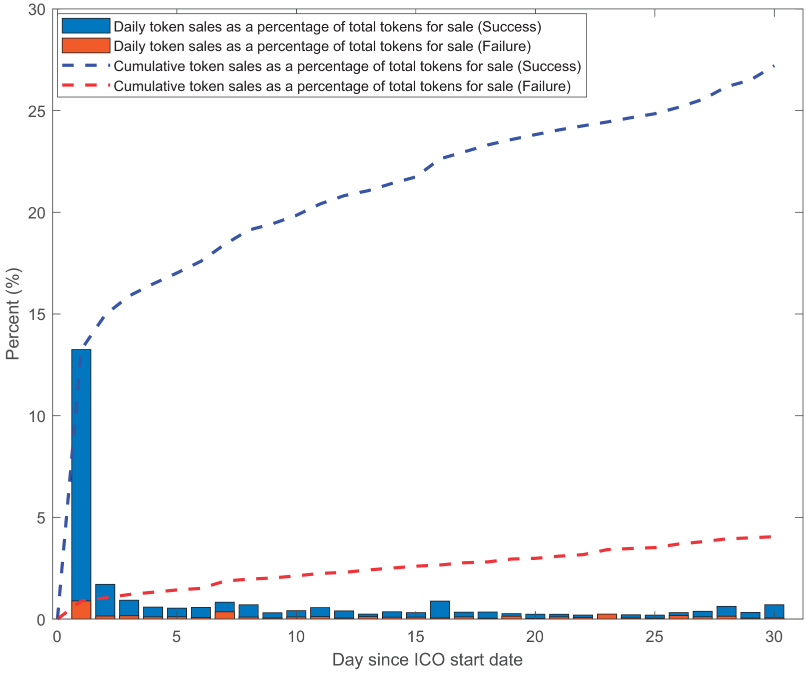

Figure 3
Primary market subscriptions in ICOs
This figure shows time series patterns of token subscriptions during ICOs that started between January 1, 2016, and December 31, 2018, and were completed as of March 31, 2019. Our sample includes all Ethereum-based ICOs that sold a positive number of tokens. The blue (red) bars plot the average daily token sales as a percentage of total tokens for sale in successful (failed) ICOs. The blue (red) dotted line plots the cumulative daily token sales as a percentage of total tokens for sale in successful (failed) ICOs. An ICO fundraiser is considered successful if its soft cap was reached or the project raised more than $0.5 million in the absence of a soft cap.

through 6). We consider the differences to be statistically significant if both the *t*-statistic (column 5) and Wilcoxon statistic (column 6) indicate a two-tail significance of at least 10%, and at least one of the two statistics is significant at the 5% level.

Regarding ex ante ICO characteristics, most importantly, successful ICOs on average have been assigned a rating of 3.4 (out of 5) by online experts, 0.5 points higher than that for failed token sales. The difference is statistically significant, suggesting that analyst certification before an ICO goes live is an important predictor of fundraising success. In the absence of traditional underwriters who play a critical intermediary role in the IPO market, analysts can potentially help reduce information asymmetry in ICOs, all of which feature decentralized fundraising platforms through blockchain technology. This is reminiscent of "crowd due diligence" in traditional crowdfunding (Agrawal, Catalini, and Goldfarb,

Table 2
ICO characteristics

	Successful ICOs			Difference between successful and failed ICOs		
	Average (1)	Median (2)	SD (3)	Diff. in avg. (4)	*t*-stat of diff. (5)	Wilcoxon (6)
Ex ante ICO characteristics						
Headline rating	3.414	3.500	0.741	0.494	19.07	18.87
No. of analysts	6.788	3.000	9.762	3.665	14.27	15.85
Soft cap ($ million)	5.046	2.229	12.242	−0.352	−0.42	−0.94
Hard cap ($ million)	57.286	20.000	513.458	18.896	1.45	3.51
Fraction of tokens for sale	0.553	0.560	0.208	−0.041	−5.75	−6.20
Presale	0.587	1	0.492	0.029	1.68	1.68
High bonus	0.322	0	0.467	−0.038	−2.31	−2.31
Know your customer (KYC)	0.402	0	0.491	0.019	1.10	1.10
Whitelist	0.268	0	0.443	0.001	0.06	0.06
Participation restriction	0.374	0	0.349	−0.014	−0.85	−0.85
Multiple languages	0.419	0	0.494	0.145	8.96	8.96
Multiple currencies	0.471	0	0.499	0.050	2.88	2.88
STO	0.024	0	0.154	0.006	1.19	1.19
Ex post ICO characteristics						
Gross proceeds ($ million)	14.680	6.579	32.613	12.654	8.44	24.38
Gross proceeds/Hard cap	0.554	0.421	0.551	0.462	16.85	23.34
No. of subscribers	2,479.583	546	5,241.620	2,302.408	12.20	20.41
Duration of offering (days)	54.322	36.000	47.590	−13.736	−8.39	−9.98

This table reports characteristics of the 1,437 successful ICO fundraisers and compares them with the 1,955 failed token sales. Our sample includes all ICOs on ICObench that started between January 1, 2016, and December 31, 2018, and were completed as of March 31, 2019. An ICO fundraiser is considered successful if its soft cap was reached or the project raised more than $0.5 million in the absence of a soft cap. *Headline rating* is the average rating (on a 1-5 scale) for an ICO by analysts on ICObench. *No. of analysts* is the number of analysts that rate an ICO on ICObench. *Soft cap* is the minimum amount of funds needed and targeted by the startup to proceed as planned, and *Hard cap* is the maximum amount of capital that it aims to gather. *Presale* is an indicator that equals one if an ICO runs a token sale event before the official crowdsale goes live and zero otherwise. *High bonus* equals one if an ICO offers a bonus of over 20% (equivalent to a discount of 16.7%) and zero otherwise. *Fraction of tokens for sale* is the number of tokens for sale divided by the total number of tokens generated. *Know your customer (KYC)* is an indicator that equals one if clients are required to provide information to confirm their identities and zero otherwise. *Whitelist* is a dummy variable that equals one if customers have to register in advance to participate in an ICO and zero otherwise. *Participation restriction* equals one if an ICO is restricted in certain countries and zero otherwise. *Multiple languages* is an indicator that equals one if the white paper or website for an ICO features more than one language and zero otherwise. *Multiple currencies* equals one if an ICO accepts multiple currencies (digital or fiat) and zero otherwise. *STO* is an indicator that equals one if an ICO offers tokens with features comparable to securities that are regulated in at least one jurisdiction and zero otherwise. *Gross proceeds* is the amount raised from investors in millions. *No. of subscribers* is the number of token buyers in an ICO. *Duration of offering* is the number of days between the ICO start and end dates. In columns 1–3, we report the averages, medians and standard deviations of characteristics for successful ICOs. Columns 4 and 5 show the differences in average characteristics between successful and failed ICOs and their associated *t*-statistics. In column 6, we report the Wilcoxon signed-rank statistics, which are asymptotically normal, for differences in characteristics between successful and failed ICOs.

2014). Successful token sales also attract significantly more analysts to initiate coverage than failed ones.

The average soft cap or minimum funding goal for successful ICOs is $5.0 million, which is similar to that set by unsuccessful fundraising campaigns. The median soft caps for both groups of ICOs are lower. The average (median) hard cap or maximum goal for a successful ICO is

$57 million ($20 million), which is not significantly higher than the amount for failed ones, based on both the *t*-statistic and the Wilcoxon statistic.

As an important governance indicator, the percentage of tokens to be sold to investors measures management's skin in a firm. Successful ICOs seek to sell 55% of generated tokens to outsiders, compared with the target of over 59% in failed ones, with the difference being significant.[20] Nearly 59% of successful ICOs include a presale before the main token sale. Presales typically are open only to institutional or high-net wealth investors, and the proceeds raised are often used to cover the costs of launching the main ICOs. To attract these early investors, entrepreneurs often provide a steeper discount in presales than in main sales. This is analogous to the analysis of informed IPO investors by Benveniste and Spindt (1989) and Biais, Bossaerts, and Rochet (2002).

Interestingly and perhaps counterintuitively, offerings with high bonuses, defined as 20% or more, are more prevalent in failed ICOs.[21] Although generous bonuses can attract investor subscriptions in early stages of an ICO, many of these token sales provide extremely high bonuses that sometimes exceed 100%. Perhaps wary investors conclude that such ICOs are potential lemons or scams.

Over 40% of successful token sales ask for customer identification, which is similar to the figure for failed ICOs. ICOs that required advance registration or restricted sales in certain countries (*Participation restriction*) achieve a success rate that is virtually identical to that of ICOs that do not require them. It is worth noting that, since Q3 2017, these features have become the industry standard. Token sales featuring multilanguage websites or white papers tend to be more successful, indicating that potential token purchasers are not based in a single country and language barriers exist. ICOs that accept multiple (digital) currencies are also more likely to succeed. STOs make up 2.4% of successful ICOs (the difference between them and failed ones is not significant).

At the bottom of Table 2, we further report several key ex post ICO outcomes. On average, successful sales raise $14.7 million.[22] Successful ICOs on average achieve 55.4% of the hard cap with nearly 2,480 supporters on average. Successful ICOs also on average involve much

[20] Unlike most IPOs in which management loses majority control of the offering firms (except some high-tech IPOs, such as Facebook and Snap, where management controls voting rights via dual class shares), in token sales management does not relinquish control as voting rights are not typically attached to tokens.

[21] Sagar (2017) considers ICO bonuses that exceed 20% a red flag. Using an alternative threshold of 30% yields consistent results in our main analysis.

[22] In contrast, according to the Crowdfunding Center, in 2016, successful crowdfunding campaigns on average raised just $29,900, a tiny fraction of the amount raised in ICOs. Specialized crowdfunding platforms, such as Kickstarter, support even smaller fundraising campaigns (Xu, 2016). On the other hand, tech IPOs in 2017 grossed over $250 million on average (Ritter, 2019).

Table 3
Analysts' ratings and fundraising success

Dependent variable:	Fundraising success			
	(1)	(2)	(3)	(4)
Headline rating	0.214***	0.194***	0.152***	0.153***
	[10.46]	[11.03]	[6.98]	[7.32]
Headline rating × High no. of analysts			0.042**	
			[2.12]	
High no. of analysts			−0.052	
			[-0.79]	
Headline rating × Analyst diversity				0.045**
				[2.14]
Analyst diversity				−0.010
				[-0.14]
Fraction of tokens for sale		−0.241***	−0.249***	−0.252***
		[−8.22]	[−8.76]	[−9.34]
Presale		0.042**	0.040**	0.037**
		[2.39]	[2.35]	[2.04]
High bonus		−0.039***	−0.038***	−0.037***
		[−3.34]	[-3.03]	[−3.03]
Know your customer		−0.005	−0.010	−0.014
		[−0.38]	[-0.74]	[−0.95]
Multiple languages		0.077***	0.072***	0.072***
		[5.65]	[5.52]	[5.34]
Multiple currencies		0.033*	0.027	0.028
		[1.78]	[1.43]	[1.56]
STO		0.149**	0.152**	0.151**
		[2.11]	[2.11]	[2.01]
Quarterly fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	3,392	3,392	3,392	3,392
Adj. R-squared	.20	.22	.22	.23
% (Dep variable = 1)	42.4%	42.4%	42.4%	42.4%

In this table, we report results pertaining to the determinants of fundraising success for all ICOs that started between January 1, 2016, and December 31, 2018, and were completed as of March 31, 2019. *Fundraising success* is an indicator that equals one if an ICO reaches its soft cap or the project raises more than $0.5 million in the absence of a soft cap and zero otherwise. *High no. of analysts* equals one when the number of analysts covering an ICO is above the sample median and zero otherwise. *Analyst diversity* is an indicator equal to one if analysts covering an ICO comprises at least one analyst with a science/tech degree, one analyst with a business/economics degree, and one analyst with another major, and zero otherwise. All independent variables are as defined in Table 2. In each column we report coefficient estimates and their t-statistics. Standard errors are clustered at the quarter level.
*$p < .1$;
**$p < .05$;
***$p < .01$

shorter durations to completion (54 days), compared with 68 days for failed cases.

4. Analysts' Ratings and ICO Outcomes

4.1 Analysts' ratings and ICO success

In Table 3, we report the results of predictive regressions where the dependent variable is fundraising success, which equals one if an ICO reaches its soft cap or the project raises more than $0.5 million in the absence of a soft cap (Mironov and Campbell, 2018).[23] The main independent variables are the same as the ICO characteristics presented in Table 2. We report coefficients derived from a linear probability model with country, industry, and quarter fixed effects.

As shown in columns 1 and 2, the headline rating has a significantly positive effect (at the 1% level) on the likelihood of a successful fundraising campaign. A one-standard-deviation increase in the headline rating is associated with an increase in the marginal probability of 14.4-15.9 percentage points. Relative to the unconditional probability of ICO success of 42.4%, the incremental probability is substantial. This finding is consistent with the positive intermediary role analysts play in a market that lacks traditional underwriters. For ICO characteristics, we obtain results that are largely similar to our sample statistics on successful versus failed ICOs.

To explore whether diversity of the analyst crowd influences the positive relationship between the headline rating and fundraising success, in column 3 we add an interaction term that consists of the headline rating and an indicator equal to one when the number of analysts covering an ICO is above the sample median. The coefficient for this interaction term is positive and statistically significant, implying that the headline rating is more informative when more analysts cover an ICO. This result suggests that the headline rating becomes more informative as it aggregates more individual analyst's ratings and that thanks to this aggregation, inaccuracies in individual ratings are more likely to be canceled out.

Alternatively, in column 4 we add a product of the headline rating and a dummy variable equal to one if the group of analysts covering an ICO comprises at least one analyst with a science/tech degree, one analyst with a business/economics degree, and one analyst with another major. We find that over 29% of the sample ICOs are covered by groups of analysts with diverse educational backgrounds and that the headline rating predicts fundraising success more strongly when the analyst group is more diverse. These results are consistent with the patterns documented by Da and Huang (2020).

As shown in Internet Appendix Table IA2, our results are qualitatively similar when replacing the fundraising success dummy with an exchange-listing indicator or the logarithm of gross proceeds that reflects the degree of fundraising success.[24] In Internet Appendix Table IA3, we show that favorable ratings are also associated with a quicker token sale, all else equal.

[23] For ICOs that do not specify a soft cap, changing the target to \$0.25 million or \$0.75 million yields similar results.

[24] Our test sample in this regression is smaller as the analysis requires specific information on gross proceeds.

Table 4
Analysts' ratings and primary market token subscriptions

Dependent variable:	First-day subscription (1)	Subscription b/t 1st and 5th days (2)	Subscription b/t 1st and 15th days (3)
Headline rating	0.032**	0.042***	0.053***
	[2.47]	[2.68]	[3.56]
Fraction of tokens for sale	−0.047*	−0.064*	−0.082**
	[-1.94]	[-1.65]	[-2.37]
Presale	−0.009*	−0.015***	−0.013***
	[-1.79]	[-2.78]	[-2.68]
High bonus	−0.017***	−0.022***	−0.026***
	[-3.73]	[-3.45]	[-3.98]
Know your customer	−0.009	−0.009	−0.013
	[-1.07]	[-0.77]	[-1.02]
Multiple languages	0.005	0.004	−0.001
	[0.47]	[0.30]	[-0.05]
Multiple currencies	−0.007	−0.011**	−0.006
	[-1.11]	[-2.06]	[-1.07]
STO	0.028	0.025	0.023
	[0.96]	[0.91]	[0.83]
Quarterly fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Observations	1,275	1,275	1,275
Adj. R-squared	.11	.11	.12

In this table, we report results indicating how analysts' ratings affect primary market investor subscriptions during initial periods of token sales for all Ethereum-based ICOs that opened between January 1, 2016, and December 31, 2018, and were completed as of March 31, 2019. The sample includes a total of 1,275 ICOs that have all the required information on ICO characteristics and primary market subscriptions. *First-day subscription* is the number of tokens subscribed on the first day divided by the number of tokens for sale. *Subscription between 1st and 5th days and Subscription between 1st and 15th days* are similarly defined. All other independent variables are as defined in Table 2. In each column, we report coefficient estimates and their t-statistics. Standard errors are clustered at the quarter level.
*$p < .1$;
**$p < .05$;
***$p < .01$

4.2 Analysts' ratings and primary market subscriptions

Now we go one step further to see how good ratings could lead to successful fundraising by looking into investor actions during the primary market subscription phase. As Figure 3 indicates, investors in successful ICOs purchase a substantial number of tokens on the first day, while in failed ICOs investors barely buy any tokens during the initial periods of an ICO. To examine whether analysts' ratings are correlated with such differences in primary market subscription patterns, we regress measures that gauge primary market subscriptions for an ICO on its headline rating and a vector of ICO-level covariates.

As reported in column 1 of Table 4, the headline rating is a strong predictor of first-day subscriptions as a percentage of the number of tokens for sale. Although we cannot rule out the possibility that both the headline rating and the aggressive first-day subscriptions are correlated with latent ICO quality factors, the predetermined headline rating variable is not subject to any reverse causality. A one-standard-deviation increase in the headline rating is associated with an increase in first-day tokens sold of 2.4 percentage points (a finding that is significant at the 5% level). This suggests that positive headline ratings help increase demand among investors in the absence of reputable underwriters in this decentralized fundraising procedure. In columns 2 and 3, the reported results further show that headline ratings also strongly predict token sales during the first 5 and 15 days of an ICO, respectively.

5. Analysts' Ratings and Investor Attention

One possible channel through which ratings affect fundraising success is that investors pay attention the ratings. Investor attention, however, is not directly observable. We therefore construct a proxy for investor attention based on message board activities on BitcoinTalk.org.

BitcoinTalk is one of the oldest and largest internet forums dedicated to the discussion of cryptocurrency and blockchain technology. It has a popular message board named *Announcements (Altcoins)*. To reach potential investors, an ICO team often makes an announcement on the message board *before* its token sale goes live. The announcement is a short summary that describes the startup and its planned ICO, and it usually includes links to the startup's website, white paper, and social media sites. Potential investors follow up and discuss various aspects of the ICO on the forum. We find that 48.4% of our sample ICOs made an announcement on BitcoinTalk.org. For each of these ICOs, we download the announcement, posts, and their respective timestamps.

We measure potential investors' response to an individual rating by counting the numbers of posts during the 7-day window before and after the rating issuance and calculating its growth rate. To make sure that our results are not driven by outliers, we use the logarithm of the count. If more than one rating is issued on a given day, we average the number of posts. To control for the timing of ratings, we include *Days elapsed since first rating*, which is the number of days elapsed since the first rating for an ICO was issued. As shown in column 1 of Table 5, the growth rate in BitcoinTalk.org posts positively responds to individual analyst's rating. A one-standard-deviation increase in the rating level is associated with a 3.2% percentage-point increase in the number of posts. The point estimate is statistically significant at the 1% level, and is robust to the inclusion of month or ICO fixed effects, as shown in columns 2 and 3. In untabulated analysis, we find that the results are consistent when we shorten the event window to a 5-day window around the analysts' rating announcement.

As the temporal reaction by potential investors is not influenced by any time-invariant ICO-level confounders, this result partly alleviates

Table 5
Analysts' ratings and investor attention

Dependent variable:	log growth rate of # of posts with 7-day window		
	(1)	(2)	(3)
Individual analyst's rating	0.036***	0.038***	0.026***
	[5.21]	[5.54]	[3.39]
Days elapsed since first rating	−0.00018***	−0.00006	−0.00162*
	[-2.69]	[-0.93]	[-1.76]
Monthly fixed effects	No	Yes	No
ICO fixed effects	No	No	Yes
Observations	8,792	8,792	8,386
Adj. R-squared	.005	.015	.118

In this table, we report results indicating whether analysts' ratings affect investor attention by merging the data from ICObench and BitcoinTalk.org. *Individual analyst's rating* is the individual analyst's rating on a given day. If more than one rating is issued on a given day, we take the average of them. *Days elapsed since the first rating* is the number of days elapsed since the first rating for an ICO was issued. By construction, *Days elapsed since the first rating* for the analyst who issued the rating first in an ICO is zero. *log growth rate of # of posts within 7-day window* is the logarithm of 1 + the number of posts during the 7-day window after the rating is issued divided by the number of posts during the 7-day window before the rating is issued. In each column, we report coefficient estimates and their *t*-statistics. Standard errors are clustered at the ICO level.
*$p < .1$;
**$p < .05$;
***$p < .01$

omitted-variable concerns of our baseline results in Section 4.1.[25] Overall, while the results are not conclusive, they collectively suggest that potential investors appear to pay attention to analysts' ratings.

6. Analyst Incentives and ICO Success

6.1 Analyst career incentives

Why do analysts issue informative ratings? Following the literature that highlights career incentives for equity and credit analysts (DeHaan et al., 2015; Cornaggia, Cornaggia, and Xia, 2016; Kempf, 2020),[26] we examine whether career concerns of ICO analysts could play a key role in incentivizing them to issue more informative ratings. Although ICO analysts do not obtain direct financial rewards for their ratings services, they are often hired as advisors in future ICOs. In our sample, 31.0% of the analysts have served as ICO advisors, and the average analyst has held 2.2 advisory positions. Conditional on analysts having served as an

[25] We note, however, that not every participant on BitcoinTalk.org may be an actual investor in a given ICO. The number of posts on this representative online forum serves as a proxy for investor attention and interest.

[26] While DeHaan et al. (2015) and Kempf (2020) highlight positive incentive effects for SEC lawyers and credit analysts' career concerns, Cornaggia, Cornaggia, and Xia (2016) emphasize that credit analysts' career concerns are related to inflated ratings.

advisor at least once, the average analyst in our sample has occupied 7.1 advisory positions in total.

According to Krawczyk (2019), an ICO advisor typically receives company tokens ranging from $25,000 to $100,000 in value plus a cash retainer. In some cases, advisors also receive a portion of the gross proceeds a company raises. In addition, advisors are typically offered investment opportunities in a company. Analysts therefore can "make the big bucks" by serving multiple advisory roles.[27]

Given that ICObench uses the number of ratings issued by an analyst as one major factor to determine her track record, we proxy for analyst reputation using the number of ratings an analyst has issued in the past or in the past 3 months. We also use "top-10 expert," a monthly designation awarded by ICObench based on analyst track records, as another measure of analyst reputation.

Table 6 reports the results. In this regression analysis, the sample starts from March 2018 so we have a sufficient number of observations regarding past rating issues. The number of ratings an analyst has issued is positively associated with the probability that the analyst holds advisory positions in the next 3 to 6 months. Similarly, the "top-10 expert" designation dummy is related to a 32.9- to 45.1-percentage-point increase in the probability of holding advisory positions.

In panel B, we repeat our analysis by replacing the dependent variable with the natural logarithm of one plus the number of advisory positions that an analyst holds in the 3 to 6 months following a rating issuance. Our results are largely unchanged: analyst reputation helps obtain lucrative advisory positions in future ICO projects, enhancing the analyst's career.[28]

6.2 Platform-driven incentives

We conduct additional analysis on how ICObench's specific feature may affect analysts' incentive to issue more informative ratings. On the platform, ratings issued by analysts with high expert scores (i.e., good track records of producing high-quality ratings in the past) are more heavily weighted than the ratings from other analysts who cover the same ICO. Moreover, ratings with the highest weights are placed at the top of the ratings section, offering greater visibility to these top analysts. Such visibility could further incentivize ICO analysts to produce more accurate ratings. In the board of directors literature, Masulis and Mobbs (2014)

[27] Jason Hung, a "top-10" analyst on ICObench, has served as an advisor to over 40 ICO firms as of October 2020, which have compensated him with more than $1 million (Krawczyk, 2019).

[28] In Internet Appendix Table IA4, we further show that when a "top-10" analyst serves as an ICO advisor, analysts who cover the ICO tend to issue more favorable ratings. These ICOs are also more likely to be successful in fundraising.

Table 6
Analyst career incentives

A. Probability of serving as an ICO advisor

Dependent variable:	Holds advisory positions in months [+3, +6]					
	(1)	(2)	(3)	(4)	(5)	(6)
log(#Ratings issued)	0.039***	0.033***				
	[4.70]	[3.91]				
log(#Ratings issued in past 3 months)			0.056***	0.046***		
			[6.97]	[5.64]		
top-10 expert					0.451***	0.329***
					[4.73]	[3.08]
Monthly fixed effects	No	Yes	No	Yes	No	Yes
Analyst country fixed effects	No	Yes	No	Yes	No	Yes
Analyst controls	No	Yes	No	Yes	No	Yes
Observations	2,596	2,544	2,596	2,544	2,596	2,544
Adj. R-squared	.04	.16	.09	.19	.07	.18

B. Number of ICO advisory positions

Dependent variable:	Log(#ICO advisory positions held in months [+3, +6])					
	(1)	(2)	(3)	(4)	(5)	(6)
log(#Ratings issued)	0.039***	0.030***				
	[3.99]	[2.93]				
log(#Ratings issued in past 3 months)			0.060***	0.049***		
			[5.87]	[4.81]		
top-10 expert					0.516***	0.364***
					[3.58]	[2.61]
Monthly fixed effects	No	Yes	No	Yes	No	Yes
Analyst country fixed effects	No	Yes	No	Yes	No	Yes
Analyst controls	No	Yes	No	Yes	No	Yes
Observations	2,596	2,544	2,596	2,544	2,596	2,544
Adj. R-squared	.03	.17	.07	.19	.06	.18

This table relates analyst experience and reputation with advisory roles in future ICOs. *log(#Ratings issued)* is the logarithm of one plus the number of ratings issued by an analyst in the past. *log(# Ratings issued in past 3 months)* is the logarithm of one plus the number of ratings issued by an analyst in the past 3 months. *Top-10 expert* is a dummy variable that equals one if an analyst is ranked among the top-10 experts by ICObench in a given month and zero otherwise. *Holds advisory positions in months [+3, +6]* equals one if an analyst holds at least one ICO advisory position between 3 and 6 months after a given month, and zero otherwise. *Log(#ICO advisory positions held in months [+3, +6])* is the logarithm of one plus the number of ICOs for which an analyst serves as an advisor between 3 and 6 months after a given month. Analyst controls include educational degrees and whether an analyst has an active LinkedIn page or Twitter account, as defined in Table 1. In each column, we report coefficient estimates and their t-statistics. Standard errors are clustered at the analyst level.
*$p < .1$;
**$p < .05$;
***$p < .01$

find that a director with multiple directorships devotes more time and effort to the board that gives maximum visibility and prestige to serve as a director. Analogous to this study, we expect that an analyst who cherishes her reputation would work harder on an ICO if her rating shows at the top of the ICO's ratings section. This relative analyst ranking in a

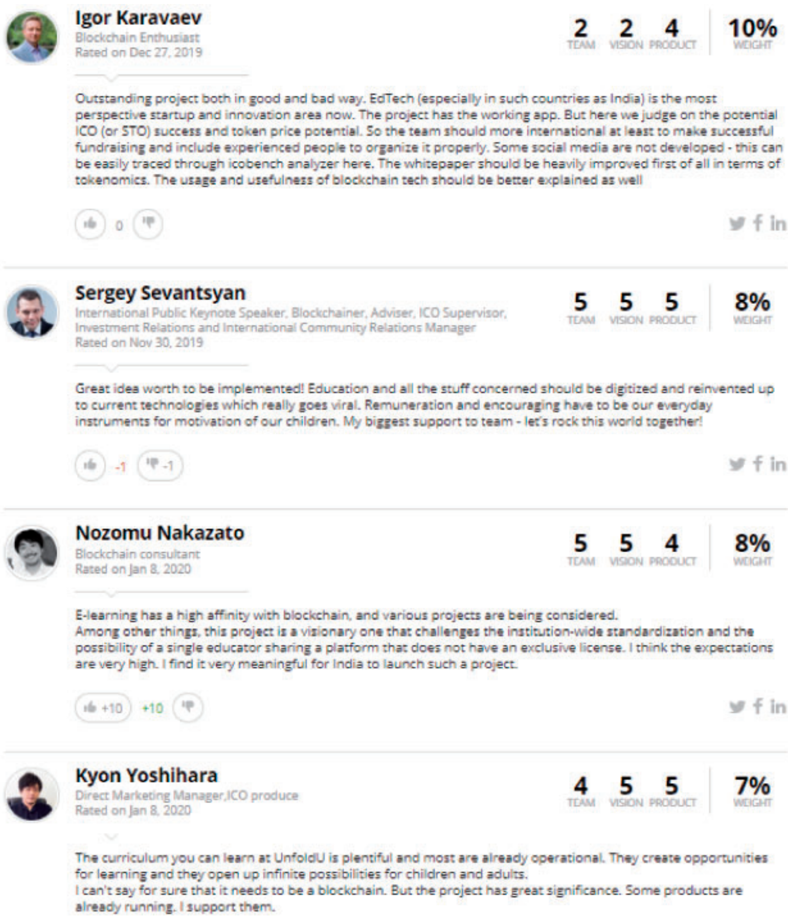

Figure 4
Visibility of analysts in an ICO
This figure shows the analysts' ratings page of *UnfoldU*, an AI-powered online education platform, on the ICObench platform. This ICO started on February 17, 2020, and ended on April 10, 2020. Space considerations limit us to presenting the top-four analysts of the 12 analysts who rated the ICO.

given ICO provides an incentive to the analyst to issue a more informed rating on the underlying project.

We illustrate this feature using the *UnfoldU* ICO, an AI-powered online education platform. As shown in Figure 4, the analyst placed at the top of *UnfoldU*'s ratings page has the highest weight, ranked using expert scores among the 12 analysts rating this ICO.[29] His rating has a weight of

[29] See Section 2.2 for more details on ICObench's expert score system.

Table 7
Platform-driven incentives of individual analysts

A. Highest visibility and revision of ratings

Dependent variable:	Revision	
	(1)	(2)
ICO with highest visibility	0.041***	0.038***
	[4.79]	[3.83]
Fraction of tokens for sale	0.003	−0.007
	[0.22]	[-0.41]
Presale	−0.005	−0.001
	[-0.75]	[-0.24]
High bonus	0.009	0.009
	[1.68]	[1.74]
Know your customer	−0.002	−0.009*
	[-0.32]	[-1.86]
Multiple languages	0.006	0.005
	[0.96]	[0.74]
Multiple currencies	−0.014*	−0.015*
	[-1.85]	[-2.05]
STO	0.006	0.014
	[0.49]	[1.01]
Analyst fixed effects	Yes	No
Quarterly fixed effects	Yes	No
Analyst×Quarterly fixed effects	No	Yes
Industry fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Observations	12,755	12,286
Adj. R-squared	.24	.28
% (Dep variable = 1)	9.4%	9.4%

B. Highest visibility and informativeness of ratings

Dependent variable:	Fundraising success	
	(1)	(2)
Individual analyst's rating	0.063***	0.061***
	[5.54]	[4.69]
Individual analyst's rating × ICO with highest visibility	0.030***	0.037***
	[5.28]	[6.62]
ICO with highest visibility	−0.143***	−0.169***
	[-4.73]	[-6.04]
Fraction of tokens for sale	−0.093**	−0.092**
	[-2.94]	[-2.80]
Presale	0.094***	0.086***
	[3.67]	[3.69]
High bonus	−0.013	−0.021
	[-0.44]	[-0.74]
Know your customer	0.049	0.049
	[1.71]	[1.81]
Multiple languages	0.064***	0.055***
	[4.23]	[3.40]
Multiple currencies	0.040	0.043
	[1.54]	[1.68]
STO	0.151***	0.142***
	[3.89]	[3.56]
Analyst fixed effects	Yes	No
Quarterly fixed effects	Yes	No
Analyst×Quarterly fixed effects	No	Yes

(continued)

Table 7
Continued

B. Highest visibility and informativeness of ratings

Dependent variable:	Fundraising success	
	(1)	(2)
Industry fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Observations	12,755	12,286
Adj. R-squared	.27	.28
% (Dep variable = 1)	67.5%	67.5%

In this table, we report results indicating whether analysts are more likely to revise their ratings and issue more informative ratings for the ICOs in which they have higher visibility. *Revision* is a dummy variable that equals one if an analyst revised his/her rating and zero otherwise. *Fundraising success* is an indicator that equals one if an ICO reaches its soft cap or the project raises more than $0.5 million in the absence of a soft cap and zero otherwise. *ICO with highest visibility* is a dummy variable that equals one if an ICO gives an analyst the highest weight and hence visibility among all analysts who cover the ICO and zero otherwise. If more than one analyst has the highest weight, we assign one to all of them. *Individual analyst's rating* is an individual analyst's rating for an ICO. All other ICO level variables are as defined in Table 2. In each column we report coefficient estimates and their *t*-statistics. Standard errors are clustered at the quarter level.
$^{*}p < .1$;
$^{**}p < .05$;
$^{***}p < .01$

10%, the highest among the 12 ratings.[30] Importantly, the same analyst may be ranked differently across ICOs, depending on his expert score relative to the score of other analysts. This indicates that the same analyst's visibility varies across ICOs.

More than 67% of the analysts in our sample cover multiple ICOs in the same quarter. For each of these analysts, we identify the ICO that gives them most visibility in the community. Our identification strategy is based on this *relative* importance of an ICO to an analyst. The relative rank is determined not only by the analyst's own track records but also by other analysts' records and, therefore, is difficult to manipulate systematically.

Analysts occasionally revise their ratings, and they do so when their previous ratings no longer accurately reflect the underlying project quality. Revising the ratings is likely to involve extra time and resources, and thus, revision can be a proxy for the analyst's extra effort in providing ratings. In Table 7, panel A, we regress *Revision*, an indicator for a revised rating on a given ICO, on *ICO with highest visibility*, a dummy variable indicating whether the ICO provides the highest visibility to the analyst. Column 1 shows that an analyst is 4.1 percentage points more likely to revise her rating if the ICO gives the analyst the highest visibility among fellow raters. In column 2, we add analyst-quarter fixed effects for

30 Because of space limitations, of the 12 analysts covering *UnfoldU*, we show only four analysts with the highest weights. These 12 weights are used to compute the headline rating.

analysts who issue multiple ratings in a given quarter. We obtain similar results.

In panel B, we proceed by regressing fundraising success of an ICO on the interaction between an individual analyst's rating and *ICO with highest visibility*. We use the most recent ratings of individual analysts. As shown in panel B of Table 7, an individual rating is more informative in predicting fundraising success if the covered ICO gives the analyst the highest visibility. The estimate is statistically significant at the 1% level. Overall, our results suggest that more powerful incentives to analysts are associated with more informative ratings.[31] In addition, these analyst-level analyses help mitigate endogeneity concerns due to potential ICO-level omitted factors that are correlated with fundraising success.

7. Post-ICO Performance

Given that ICO fundraising is only the first step toward a successful blockchain-based project, it is crucial to analyze how analysts' ratings predict post-offering token performance over longer horizons.

7.1 Potentially fraudulent ICOs

While ICOs have been promoted as a new investment opportunity, they also bring increased risk of fraud and manipulation as this "Wild West" market is less regulated than conventional markets. Hence, we examine whether analysts' ratings are also useful for predicting ICO fraud, which is typically uncovered months or even years post-ICO. In Appendix C, we provide an example of a genuine ICO and another example of a fraudulent token sale.

7.1.1 ICOs with missing white papers. Our first proxy for potential fraud is whether an ICO removes its white paper. To go dark without leaving a trace, fraudulent ICOs often pull their white papers immediately after the sales are concluded or even during a sale. Note that the going-dark status of an ICO is not mechanically correlated with our average analysts' rating as the ratings are issued prior to the token sales. We examine the characteristics of the 262 ICOs that removed their white papers. As shown in column 1 of Table 8, analysts ex ante issue a significantly lower rating for ICOs with missing white papers. These ICOs also exhibit lower governance quality, because insiders have less skin in the game and they tend to offer more generous bonuses. The token sales are also less likely to feature multilanguage websites. In Internet

[31] One concern about the analysis in Table 8, panel B, is whether the analyst with the highest visibility knows when issuing the rating that she eventually will be most visible in the ICO. We discuss this timing issue in depth in Internet Appendix 1.

Table 8
Analysts' ratings and fraudulent ICOs

Dependent variable:	Missing white paper		Charged by regulators	
	(1)	(2)	(3)	(4)
Headline rating	−0.058***	−0.052***	−0.006*	−0.006*
	[-4.54]	[-4.52]	[-1.76]	[-1.65]
Fraction of tokens for sale		0.050*		0.010*
		[1.95]		[1.78]
Presale		−0.024***		0.005
		[-3.38]		[1.40]
High bonus		−0.006*		−0.004
		[-1.92]		[-1.37]
Know your customer		0.009		−0.011**
		[1.28]		[-2.34]
Multiple languages		−0.032***		0.001
		[-3.51]		[0.45]
Multiple currencies		−0.005		0.006***
		[-1.00]		[3.23]
STO		−0.008		0.017
		[-0.35]		[1.27]
Quarterly fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	3,392	3,392	3,392	3,392
Adj. R-squared	.06	.07	.02	.02
% (Dep variable = 1)	7.7%	7.7%	1.2%	1.2%

In this table, we report results pertaining to the determinants of potentially fraudulent ICOs. *Missing white paper* is an indicator that equals one if an ICO does not have a downloadable white paper and zero otherwise. *Charged by regulators* is a dummy variable that equals one if an ICO is charged by U.S. regulators for fraud. All independent variables are as defined in Table 2. In each column we report coefficient estimates and their *t*-statistics. Standard errors are clustered at the quarter level.
*$p < .1$;
**$p < .05$;
***$p < .01$

Appendix Table IA5, panel A, we show evidence that ICOs missing white papers have a significantly lower fundraising success rate, raise less funds, and are less likely to be listed.

7.1.2 ICOs charged by regulators. Although ICOs that pulled white papers are more likely to be fraudulent, it is difficult to ascertain that they must be scams. We thus repeat our analysis using ICOs, such as AriseBank and Centra Tech, that involved ex post fraud allegations by U.S. regulators. In column 2 of Table 8, panel B, we report that analysts ex ante assign a lower rating to alleged fraudulent ICOs. Moreover, the fraudulent ICOs are less likely to require a KYC procedure and the insiders retain fewer tokens. In Internet Appendix Table IA5, panel B, we report that prosecuted ICOs are less likely to achieve fundraising success or be listed. They also raise less money as a fraction of the hard cap.

Table 9
Token performance

	Average (1)	25th percentile (2)	Median (3)	75th percentile (4)	SD (5)	Obs. (6)
Token returns						
First-day return	112.0%	−63.7%	−10.1%	83.3%	526.9%	811
Three-month return	44.1%	−73.0%	−45.0%	19.3%	267.4%	765
Six-month return	81.3%	−87.3%	−67.7%	2.9%	519.1%	699
One-year return	71.4%	−95.3%	−84.8%	−30.7%	720.7%	430
First-day excess return	109.8%	−45.9%	−8.9%	74.8%	521.0%	811
Three-month excess return	21.7%	−63.0%	−34.7%	14.0%	248.5%	765
Six-month excess return	45.0%	−57.0%	−36.6%	−3.2%	475.5%	699
One-year excess return	−4.5%	−96.9%	−26.8%	−16.1%	560.5%	430
Return volatility and delisting						
Three-month volatility	329.8%	203.5%	264.7%	365.9%	259.7%	765
Six-month volatility	300.8%	195.3%	249.7%	341.1%	184.9%	699
One-year volatility	272.1%	185.1%	224.2%	294.8%	169.6%	430
Delisting in 3 months	0.008	0	0	0	0.088	771
Delisting in 6 months	0.026	0	0	0	0.160	718
Delisting in 1 year	0.081	0	0	0	0.273	468

In this table, we report statistics pertaining to returns, return volatility, and delisting for all listed tokens that were sold through an ICO between January 1, 2016, and December 31, 2018. The number of observations varies whether information is available. *First-day return* is measured from the token offer price to the first trading day closing price. *Three-month return, Six-month return, and One-year return* are measured from the first after-market closing price to closing prices on the 91st, 182nd, and 365th trading days, respectively. Three-month, 6-month, and 1-year returns all exclude first-day returns. An excess return is calculated as the raw return minus the corresponding compounded daily return on the value-weighted index of Ethereum and Bitcoin. *Three-month volatility, Six-month volatility*, and *One-year volatility* are defined as annualized realized volatility within 3 months, 6 months, and 1 year after being listed on CoinMarketCap, respectively. *Delisting in 3 months* is a dummy variable that equals one if a token is delisted from CoinMarketCap within 3 months after being listed and zero otherwise. *Delisting in 6 months and Delisting in 1 year* are similarly defined.

Overall, in Table 8, we find suggestive evidence that analysts are also able to detect potentially fraudulent ICOs ex ante and issue lower average ratings for them. Although certain analysts could be hired by insiders to inflate the ratings, they are able to warn investors about potential lemons in the cross-section. We also find that potentially fraudulent token sales have a lower governance quality in general.

7.2 Long-run performance

In Table 9, we summarize token returns for various horizons. Starting with the 6-month period, the median token return after the first exchange trading day significantly underperforms the benchmark return on ETH and BTC by 36.6 percentage points, while the average 6-month excess return is highly positive at 45%. These statistics indicate that token returns over this relatively long horizon are highly skewed. For the 1-year horizon, we find that the median return is negative, −26.8% (a finding that is significant at the 1% level), while the average excess return is not significantly different from zero. In terms of the order of magnitude, these return statistics are consistent with those reported by

Table 10
Analysts' ratings and long-run token performance

Dependent variable:	Three-month return		Six-month return		One-year return	
	OLS (1)	Median regression (2)	OLS (3)	Median regression (4)	OLS (5)	Median regression (6)
Headline rating	0.209*	0.057	0.313**	0.089**	0.397***	0.081**
	[1.76]	[1.62]	[2.01]	[2.08]	[2.99]	[2.44]
Fraction of tokens for sale	0.531*	−0.124	0.822	−0.021	0.141	0.046
	[1.70]	[−0.73]	[1.08]	[−0.29]	[0.57]	[0.27]
Presale	−0.189	−0.082*	−0.125	−0.010	−0.655***	−0.008
	[−1.29]	[−1.87]	[−1.26]	[−1.21]	[−3.51]	[−0.59]
High bonus	−0.275***	−0.053	−0.068	−0.002	−0.811***	−0.018
	[−2.64]	[−1.28]	[−0.38]	[−0.17]	[−3.66]	[−0.39]
Know your customer	0.046	0.054	−0.058	0.035	−0.211	−0.008
	[0.25]	[0.59]	[−0.30]	[0.97]	[−0.43]	[−0.12]
Multiple languages	−0.495**	−0.021	−0.311*	0.012	−0.300***	−0.012
	[−2.56]	[−0.37]	[−1.68]	[0.47]	[−2.64]	[−1.21]
Multiple currencies	−0.112	−0.011	−0.086	0.019*	−0.004	0.034***
	[−0.84]	[−0.56]	[−0.47]	[1.84]	[−0.03]	[20.37]
STO	−0.387	0.237	−0.283	−0.100	0.158	0.066
	[−0.58]	[0.23]	[−0.52]	[−0.26]	[0.24]	[0.17]
First-day excess return	−0.100***	−0.028***	−0.094**	−0.018***	−0.080*	−0.003
	[−5.28]	[−2.98]	[−2.18]	[−6.91]	[−1.64]	[−0.83]
Three-month market return	1.055***	0.721***				
	[7.05]	[4.15]				
Six-month market return			1.705***	0.858***		
			[4.46]	[5.61]		
One-year market return					0.308***	0.412***
					[3.33]	[4.54]
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	765	765	699	699	430	430
Adj. R-squared	.15		.38		.36	
Pseudo-R-squared		.12		.19		.29

In this table, we report return patterns for all listed tokens that were sold through an ICO between January 1, 2016, and December 31, 2018. The number of observations varies depending on whether information is available. *Three-month return, Six-month return*, and *One-year return* are defined as in Table 9. Three-month, 6-month, and 1-year returns all exclude first-day returns. *First-day excess return* is calculated as the raw first-day return minus the return on the value-weighted index of Ethereum and Bitcoin. Market returns are the value-weighted Ethereum and Bitcoin index returns for the same return intervals as the dependent variables. All other independent variables are as defined in Table 2. A median regression is a quantile regression for estimating the conditional median function. In each column, we report coefficient estimates and their bootstrapped *t*-statistics.
*$p<.1$;
**$p<.05$;
***$p<.01$

Benedetti and Kostovetsky (2021). When using the top-10 digital currencies' value-weighted return as an alternative market benchmark, we obtain similar results.[32]

We now analyze the long-run performance of ICOs using both ordinary least squares (OLS) and quantile regressions that rely on medians to

[32] Since ICOs are a recent phenomenon, 47% of the listed tokens in our sample do not have a history of more than one year. Thus, we have fewer observations of 1-year returns than of returns over shorter horizons.

alleviate potential outlier concerns. These are cross-sectional regressions. In columns 1–6 in Table 10 we report the results of a multiple regression using the raw 3-month, 6-month, and 1-year total returns as the dependent variables. In addition to headline ratings, we include as additional control variables the market-adjusted first-day return, the cryptocurrency market returns, and other ICO characteristics. We also control for quarter, industry, and country fixed effects in all specifications. These are similar long-run performance regressions performed by Ritter (1991) for IPO markets. As the regression residuals are likely non-normal, we compute bootstrapped *t*-statistics. For similar distributional reasons, we focus our discussion on the median regression results reported in columns 2, 4, and 6.

For all three horizons, long-run returns are inversely related to initial returns, exhibiting potential mean reversions. Most importantly, we find that a good headline rating significantly predicts positive returns over the three horizons. Both the economic and statistical significance is greatest for the 1-year horizon. For example, a one-point increase in the headline rating is associated with an 8.1-percentage-point increase in 1-year returns, all else being equal. Recall that analysts' ratings focus on team, vision, and product, all of which are long-term indicators of underlying startup quality. This implies that analysts' ratings could indeed be informative in the long run, well beyond its predictability for fundraising success during the fundraising phase. Importantly, this long-run analysis effectively rules out a self-fulfilling equilibrium in the fundraising stage, in which investors blindly follow analysts' ratings who might issue biased ratings. As ICO investors learn more about a project's developmental progress in the long run, such short-run deviations are unlikely to survive. Our result is also consistent with key findings reported in Jia et al. (2018), who use a sample of Chinese IPOs, and find that analyst coverage and earnings forecast optimism for an IPO before it starts is positively associated with IPO long-run performance. Among the additional covariates, we also find that ICOs accepting multiple currencies tend to show higher long-run performance.

7.3 Token volatility and delisting

In addition to returns, we analyze alternative long-run performance metrics for ICOs, namely, token return volatility and delisting. CoinMarketCap delists tokens that have crashed to near-zero prices across major cryptocurrency exchanges. To estimate annualized volatility, we take the standard deviation of the log daily return and multiply it by 365 to obtain returns for the 3-, 6-, and 12-month periods after a token is listed. Listed tokens trade 365 days a year.

Table 11
Analysts' ratings, token volatility, and delisting

Dependent Variable:	Three-month volatility (1)	Six-month volatility (2)	One-year volatility (3)	Delisting in 3 months (4)	Delisting in 6 months (5)	Delisting in 1 year (6)
Headline rating	−0.453***	−0.363**	−0.228***	−0.014**	−0.037***	−0.089**
	[-3.68]	[-2.57]	[-3.63]	[-2.93]	[-4.33]	[-2.59]
Fraction of tokens for sale	0.131	0.088	0.089	−0.027	−0.019	0.001
	[0.44]	[0.39]	[0.21]	[-1.77]	[-0.57]	[0.02]
Presale	0.0509	0.0653	−0.092	−0.009	0.002	0.002
	[0.39]	[0.49]	[-0.70]	[-1.10]	[0.23]	[0.08]
High bonus	0.225	0.224	0.258	−0.002	−0.011	−0.013
	[0.93]	[1.16]	[0.89]	[-0.15]	[-0.38]	[-0.42]
Know your customer	0.269	0.0570	−0.200	0.011	−0.005	−0.009
	[1.62]	[0.71]	[-1.20]	[1.49]	[-0.46]	[-0.63]
Multiple languages	−0.348*	−0.240	−0.056	−0.009	−0.029**	−0.042**
	[-1.87]	[-1.27]	[-0.35]	[-1.38]	[-1.98]	[-2.52]
Multiple currencies	0.165	0.140	0.054	0.016**	0.020*	−0.000
	[1.56]	[0.92]	[0.34]	[2.26]	[1.82]	[-0.01]
STO	−0.105	−0.064	0.325	−0.007	−0.057***	−0.110*
	[-0.29]	[-0.21]	[0.89]	[-0.44]	[-3.84]	[-2.14]
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	765	699	430	771	718	468
Adj. R-squared	.20	.22	.22	.00	.01	.14
% (Dep variable =1)	N/A	N/A	N/A	0.01	0.03	0.08

In this table, we report results pertaining to return volatility and delisting for all listed tokens that were sold through an ICO between January 1, 2016, and December 31, 2018. *Three-month volatility, Six-month volatility*, and *One-year volatility* are defined as annualized realized volatility within 3 months, 6 months, and 1 year after being listed on CoinMarketCap, respectively. *Delisting in 3 months* is a dummy variable that equals one if a token is delisted from CoinMarketCap within three months after being listed and zero otherwise. *Delisting in 6 months and Delisting in 1 year* are similarly defined. All independent variables are as defined in Table 2. In each column, we report coefficient estimates and their *t*-statistics. Standard errors are clustered at the quarter level.
*$p < .1$;
**$p < .05$;
***$p < .01$

As shown in Table 11, more favorable headline ratings are associated with lower token return volatility over the 3-, 6- and 12-month horizons, all else remaining equal. More stable token prices increase tokens' desirability as a medium of exchange on platforms. Higher headline ratings also predict a lower probability of being delisted by CoinMarketCap over the various horizons. All these estimates are statistically significant at the 5% level, while few other control variables appear to meaningfully predict return volatility or token delisting.

8. Conclusion

This is the first study to examine whether and how online analysts help mitigate information asymmetry in fundraising campaigns that lack financial intermediation. We find that favorable ratings by a group of analysts with diverse backgrounds are associated with aggressive initial token subscriptions, ICO fundraising success, and long-run token returns.

In addition, analysts' ratings predict potential fraud and token-price volatility, both of which have received considerable attention from regulators and market participants. These are two major indicators for gauging the sustainability of the token-based crowdfunding method. Overall, our results suggest a positive information intermediary role played by online analysts in financing blockchain-related startups.

Blockchain-based fundraising has evolved rapidly, with STOs and IEOs taking center stage since late 2018 (while a surge in cryptocurrency prices during the COVID-19 pandemic has revived the ICO market). Analysts continue to cover these alternative token sale methods. Understanding the role of ICO analysts over the boom and bust cycle is, therefore, useful for designing crowdfunding platforms that strive to achieve a higher level of informational efficiency.

Appendix

A. A Changing Regulatory Environment

During the past few years, ICOs and cryptocurrency exchanges have operated in a legal and regulatory gray area. The first regulatory warning came from the SEC in July 2013, in the form of an investor alert about Ponzi schemes that involved Bitcoin and other virtual currencies. Since then, the SEC has issued a series of warnings suggesting that many token sales may have violated U.S. securities laws, including a July 2017 Report of Investigation that determined the Ethereum-based DAO tokens were securities, and offers and sales of the DAO tokens were subject to the federal securities laws. In addition to issuing dozens of subpoenas and information requests in February 2018 to technology startups involved in ICOs, the SEC charged a number of fraudulent ICOs, such as AriseBank and Centra Tech. In May 2018, more than 40 state and provincial jurisdictions in the United States and Canada announced one of the largest coordinated series of enforcement actions to crack down on fraudulent ICOs, resulting in almost 70 open investigations and 35 pending or completed enforcement actions.

Through these regulatory actions, the SEC has made clear that (1) ICO issuers must be able to demonstrate that their tokens are not securities or that they follow securities laws, and (2) market participants must ensure that their cryptocurrency activities do not undermine their antimoney laundering and KYC obligations. In April 2019, the SEC published a nonlegally binding framework for analyzing whether a token sold through an ICO qualifies as a security.[33]

Among major economies, China appears to be the most stringent cryptocurrency regulator, banning ICOs and shutting down exchanges in September 2017. The crackdown has recently broadened to Bitcoin mining, forcing some of the industry's biggest players to shift operations overseas. In neighboring South Korea, securities officials in January 2018 disallowed anonymous accounts from trading cryptocurrencies, after banning ICOs in late September 2017. European Union (EU) countries, together with Switzerland, Singapore, and Japan, have taken a relatively friendly stance toward cryptocurrency regulation.

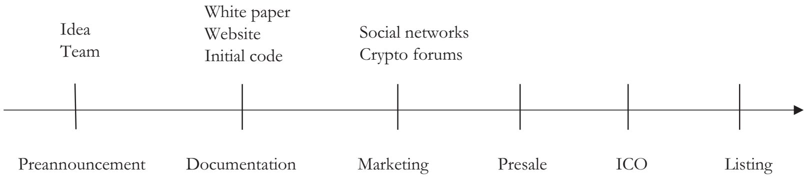

Figure A1
An illustration of the ICO timeline
This timeline illustrates the timing of events for a typical ICO. A preannouncement usually is a summary featuring the idea and team for a startup to the cryptocurrency community to gather interest and feedback. The documentation stage typically involves posting a white paper on the startup's website that describes the business model and technical specifications of the project. Many startups also publish initial codes for their ICOs. The ensuing marketing campaign often uses cryptocurrency forums and social networking sites, such as Medium, Steemit, Reddit, and Twitter. Before the official ICO goes live, there may be an optional presale of tokens. After an ICO, tokens may be listed on exchanges.

33 The SEC's Framework for "Investment Contract" Analysis of Digital Assets is available through https://www.sec.gov/files/dlt-framework.pdf.

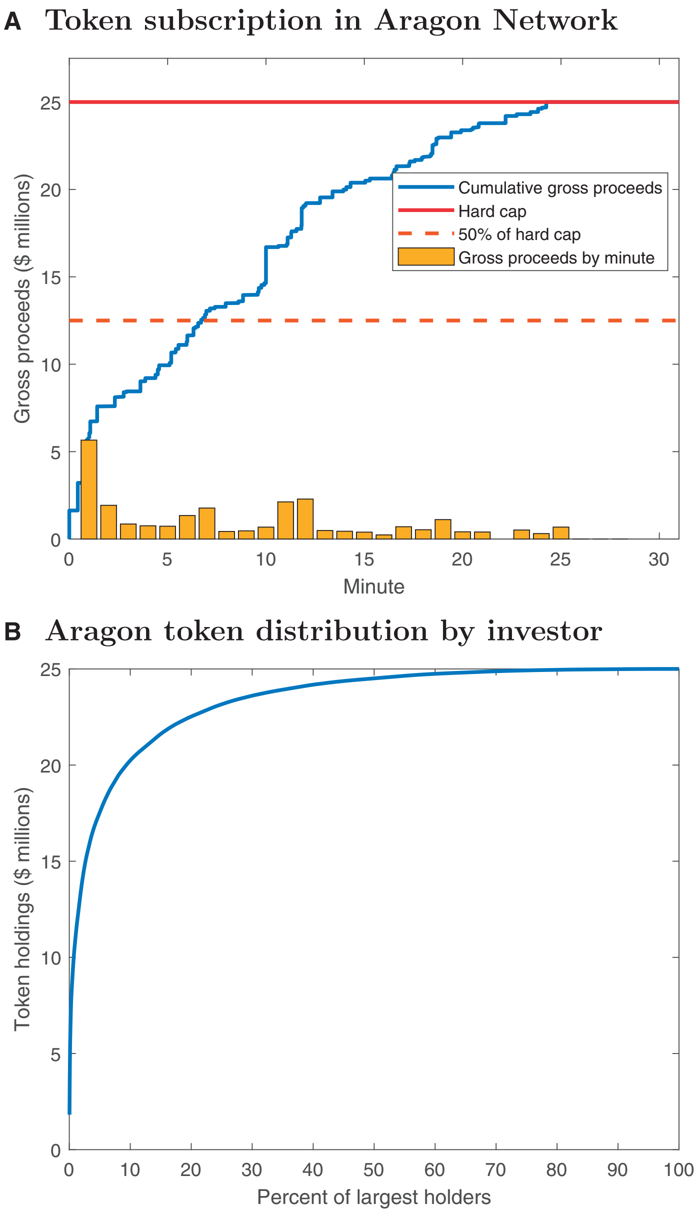

Figure A2
The Aragon token sale
Panel A shows time series patterns of token subscriptions for Aragon Network, an ICO that concluded under 31 minutes. The orange bars plot the gross proceeds ($ million) by minute during the sale and the blue line plots the cumulative gross proceeds ($ million). The red line and red dotted line plot the hard cap and 50% of the hard cap, respectively. In panel B, the blue curve plots the cumulative tokens held by the percentage of the largest holders.

Table A.1
Differences between ICOs and IPOs

	ICO	IPO
1. Preannouncement	Announce a summary featuring the idea and team to the cryptocurrency community to gather interest and feedback	Hire an investment bank to underwrite the IPO
2. Documentation	• White paper • Website • Initial code	Filings with the securities regulator • Registration statement • Prospectus
3. Marketing	Public relations campaign • Crypto forums • Social network sites, such as Medium, Steemit, Reddit, and Twitter	Road show • Meeting with potential investors • Bookbuilding by the underwriter • Offer price set
4. The sale	Subscribers send cryptocurrencies and/or fiat currencies to a digital address. Smart contracts issue tokens based on the exchange ratio.	Shares are allocated to investors
5. Listing	Tokens are listed on a cryptocurrency exchange	Shares are listed on a stock exchange

This table describes the main differences between ICOs and IPOs at each stage of the fundraising process.

However, in April 2018 the EU approved a rule that requires cryptocurrency exchanges to register with authorities and apply due diligence procedures, including a KYC policy. In January 2019, the European Securities and Markets Authority issued advice on ICOs, finding that while some tokens qualify as securities under the existing regulations, others do not.

Because of such regulatory pressure and demand from cryptocurrency exchanges to combat money laundering, startups that launch ICOs increasingly ask their clients who participate in token sales to go through a KYC process. Many recent ICOs have routinely prevented investors in the United States, China, and certain other countries from participating in their offerings.

B. The Evolution of Token Sales

Regulatory scrutiny, high-profile fraud cases, and the fall in digital currency prices have likely contributed to the dramatic cooling of the ICO market. According to ICObench (2019), ICOs raised just $902 million in Q1 2019, about 14% of all funds raised in Q1 2018. However, it is not yet clear whether this is a lull in the market or the beginning of the end for token sales and we observe new forms of fundraising emerged to mitigate the information asymmetry and governance issues in ICOs.

Since 2018, a growing number of startups have structured their token sales as STOs. Security tokens issued through STOs are regulated securities and accepted within at least one jurisdiction. Compliance requirements, such as antimoney laundering and KYC policies, can be automated within an STO system, as well as dividend management and distribution procedures.

Table A.2
ICOs by country and industry

A. Most popular countries of incorporation

Country	No. of ICOs	% of total	Fundraising success rate (%)
United States	451	13.3	42.1
Singapore	334	9.8	51.8
United Kingdom	301	8.9	38.5
Russia	242	7.1	33.9
Switzerland	174	5.1	54.0
Estonia	169	5.0	45.6
China (including Hong Kong)	150	4.4	48.0
Germany	77	2.3	39.0
Canada	72	2.1	44.4
Australia	72	2.1	38.9
Sum of the above	2,042	60.2	43.8
Total (all countries)	3,392	100	42.4

B. Most popular industries

Industry	No. of ICOs	% of total	Fundraising success rate (%)
Financial services	407	12.0	46.2
Exchanges and wallets	222	6.5	41.4
Investment	185	5.5	43.2
Blockchain infrastructure	178	5.2	59.0
Gaming and virtual reality	161	4.7	47.2
Trading	157	4.6	52.2
Social media and communication	145	4.3	40.0
Commerce and retail	143	4.2	35.0
Business services and consulting	140	4.1	43.6
Marketing and advertising	137	4.0	45.3
Sum of the above	1,875	55.2	45.4
Total (all industries)	3,392	100	42.4

This table provides descriptive statistics on ICOs from top-10 countries of incorporation in panel A, and from top-10 industries in panel B. We identify ICOs through ICObench, a data provider that specializes in ICO analytics. Our sample includes 3,392 ICOs that started between January 1, 2016, and December 31, 2018, and were completed as of March 31, 2019. In both panels, we report the number and proportion of ICOs within each country/industry, and the associated fundraising success and listing rates. An ICO fundraiser is considered successful if its soft cap was reached or the project raised more than $0.5 million in the absence of a soft cap. Information on exchange listing is reported by CoinMarketCap.

With the downfall of ICOs in 2019, the crypto fundraising industry has witnessed another form of token sales, namely, IEOs. In an ICO, investors keen in contributing to the startup send funds to the smart contract governing the ICO. The process is the same for an IEO, except that users are required to create an account with the participating cryptocurrency exchange(s), which raise funds on behalf of the issuer, while undertaking necessary commitments and performing due diligence. Tokens issued through an IEO are immediately tradable after issuance. With their reputation at stake, participating exchanges also can be incentivized to perform necessary due diligence, which could filter out dubious projects with little or no potential, hence alleviating the risks investors have to bear as compared to that of a traditional ICO.

Importantly, ICO analysts continue to issue ratings on IEOs and STOs. The average number of analysts covering an IEO or STO is comparable to the number of analysts covering an ICO, which suggests that analysts continue their intermediary role in the rapidly changing environment of token economy.

C. Two Examples of ICOs

To give the reader a flavor of how an ICO actually works, we provide a description of two ICOs. The first ICO illustrates features of successful ICOs, while the second highlights issues associated with a failed fundraiser.

C.1 The Aragon Token Sale

Founded by Luis Cuende and Jorge Izquierdo in Spain, the Aragon Network is a decentralized application built on the Ethereum Blockchain that allows users to create and manage decentralized companies. It enables users to implement basic features, such as governance, fundraising, payroll, and accounting, among other features. Aragon also includes a token (ticker ANT), which grants voting rights for making decisions about the direction of future development.

Aragon published a white paper in both English and Chinese on April 20, 2017, introducing its business model, functioning of the organization and features of the token.[34] Aragon is among the few ICOs that require a relatively long vesting period for founders, who will vest 25% of their tokens every 6 months after the sale (2-year vesting with 6-month cliffs). Aragon is also a leading startup that publishes how it uses the funds raised, detailing each expenditure on its website, including the addresses of the company's accounts and the vendors'.[35]

On the same day, the token sale was officially announced in a blog post on Aragon's website. The sale was originally planned for 4 weeks, from May 17 to June 14, 2017. Aragon sought to sell 70% of tokens to investors, and accepted only ETH. In the first 2 weeks, one ANT token was priced at 0.01 ETH (equivalent to $0.90 on May 17, 2017), and the price would increase to 0.015 ETH per token in the remaining weeks. Aragon also implemented a hidden cap of 275,000 ETH (or roughly $25 million), which was not revealed at the time of the sale.

Because of overwhelming demand, the hard cap was reached in about 30 minutes and the sale ended. There were 6,593 transactions from 2,616 unique addresses, spanning 134 Ethereum blocks. Proposed transactions valued over $8 million did not go through before the sale ended. Figure A2, panel A, plots minute-by-minute investor contributions and the cumulative contributions, which indicates that within 7 minutes Aragon raised over half of the hard cap. Panel B shows the value of tokens held by top investors. The top 10% of holders purchased about 80% of sold tokens. ANT began trading the next day, May 18, 2017, with an opening price of $1.49 per token and closing price of $1.52. The closing price on May 18, 2018, one year later, was $3.99.

C.2 Ebitz's ICO

In November 2016, a group of self-described "ethical hackers" announced the launch of Ebitz cryptocurrency, a clone version of ZCash, the 23st largest cryptocurrency by market value. Both platforms aim to protect privacy by publishing only each transaction ID on a public blockchain, but information on the sender, recipient, and amount of the transaction remains private. Unlike ZCash, however, Ebitz did not support large rewards to the founders or the standard consensus-based mining algorithm. The Ebitz ICO went live on November 28, 2016, and would end on December 26, 2016, or when the hard cap of 500 BTC was reached.

[34] Aragon's white paper is available through https://github.com/aragon/whitepaper.

[35] Each post-ICO expenditure Aragon incurs can be viewed through http://transparency.aragon.one/#/. Aragon stated that it would use the funds raised to further develop its software, implementing security audits, and hiring additional developers and operational staff.

Ebitz planned to sell 95% of the 21 million emitted tokens to participants, while allocating the remaining 5% to developers and bounty programs. The platform offered an annual interest of 3% to its token holders. The ICO accepted both BTC and ETH as valid currencies for payment. Participants who invested during the first 2 days were promised a 25% early-bird bonus, while it was fixed at 20% for the remainder of the week. Bonuses for the second and third weeks were 15% and 10%, respectively.

Two days after the sale started, an investor revealed on BitcoinTalk that the email server for Ebitz actually belonged to the domain of Opair, a dubious platform that promoted a decentralized debit card system using its own token. The Opair platform was shut down in the summer of 2016 after users discovered that some team members' profiles were fabricated.

Ebitz's website was quickly removed. However, the ICO still managed to raise about 200 BTC which were valued at $156,000 at the time. There was some speculation that these BTC mostly came from the developers themselves in an attempt to start a cascade and entice outside investors to purchase their tokens. This is reminiscent of pump-and-dump schemes targeting cryptocurrencies (Li, Shin, and Wang, 2018).

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