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

Jongsub Lee[†] Tao Li[‡] Donghwa Shin [§]

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Abstract

Certification by online analysts on a FinTech platform that harnesses the "wisdom of crowds" is associated with successful initial coin offerings (ICOs). Using novel data on ICO analysts' backgrounds, we show that more favorable ratings by analysts with proper expertise significantly predict fundraising success. Analyst ratings also help detect potential fraud ex ante. We document that analysts are incentivized to issue informative ratings to advance their careers in future ICOs. Analyst ratings positively predict long-run token returns and negatively predict return volatility. Overall, our results suggest that a market-based certification process that builds on the expertise and incentives of analysts is at play in financing blockchain startups.

Keywords: Crowdsourcing, Wisdom of Crowds, ICO, Blockchain, FinTech, Analyst expertise, Analyst incentives

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†Associate Professor of Finance, Seoul National University (SNU) Business School, South Korea. E-mail: `jongsub.lee@snu.ac.kr`. Webpage: `www.jongsublee.com`.

‡Assistant Professor of Finance, Warrington College of Business, University of Florida, USA. E-mail: `Tao.Li@ufl.edu`. Webpage: `https://site.warrington.ufl.edu/tao-li`.

§Corresponding author. Assistant Professor of Finance, Kenan-Flagler Business School, University of North Carolina at Chapel Hill. E-mail: `Donghwa_Shin@kenan-flagler.unc.edu`. Webpage: `https://sites.google.com/view/dshin`.

1 Introduction

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. In such initial offerings, information asymmetry between an entrepreneur and outside investors is an inherent problem that could hinder successful fundraising (e.g., Rock, 1986). Lacking traditional governance mechanisms, investors are also concerned about sustainable long-term platform building. Without reputable financial intermediaries, these concerns are unlikely to be resolved.

In the blockchain-based crowdfunding model adopted by ICOs, however, traditional financial intermediation is absent by design, thanks to the decentralized bookkeeping enabled by blockchain networks. Who can play the certification role of financial intermediaries, and what incentivizes the players to make good faith efforts? These important questions help us understand how to mitigate the information asymmetry associated with this new form of fundraising.

In this paper, we study the effectiveness of the "wisdom of crowds", the collective action of a group of individuals rather than advice from a single expert, using the ICO market as a laboratory. The "wisdom of crowds" phenomenon is increasingly common among FinTech platforms and therefore, our findings 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 helps screen out "lemons" (Akerlof, 1970) in the ICO market. While the diverse opinions of multiple online 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" works in the ICO setting. 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. It is therefore not clear whether these analysts fully understand the financial transactions involved in an ICO. Despite these institutional differences, we find strong evidence that ICO analysts play a positive intermediary role in harnessing the "wisdom of crowds."

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 information that we manually collect from other publicly available sources when ICObench data are incomplete or missing. We further collect from ICObench individual ratings issued by online analysts *before* an ICO starts. These predetermined ratings enable us to examine whether and how analyst ratings affect the likelihood of fundraising success in which an ICO reaches its minimum fundraising target ("soft cap") and eventual exchange listing, another milestone for successful token sales. To further shed light on fraudulent behavior involving token sales, we collect information on ICOs that were subsequently charged by U.S. regulators with fraud. 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]

Our main analysis consists of two parts. In the first part, we study the informativeness of *headline* analyst ratings that combine individual ratings at the ICO level in predicting the fundraising success and subsequent exchange listing of the offered tokens. We also test whether the average analyst rating predicts the downside outcome of an ICO using novel fraud data. In the next part, we explore the heterogeneity of analysts' characteristics and examine how their expertise and incentives affect ratings quality. These analyst-level variables and the accompanying analyses also help mitigate endogeneity concerns associated with ICO-level omitted variables that could confound our baseline results.

We find that the probability of a successful fundraising campaign increases by 13.1 percentage points (relative to the unconditional success probability of 42.4%) given a one-standard-deviation increase in the average analyst rating when controlling for various ICO characteristics. Our results largely hold when we replace fundraising success with exchange listing, an alternative success measure for ICOs, or total gross proceeds. Given that the information sources (e.g., whitepapers) that ICO analysts rely on are largely nonfinancial and technical, our result

[1] While a recent study by Howell et al. (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.

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.

Next, we examine what makes the ratings issued by ICO analysts informative and what incentivizes them to participate and produce high-quality ratings. We posit that analysts with science or technology backgrounds are more likely to understand the important technical issues associated with the underlying blockchain projects and, therefore, generate more useful insights for investors. Specifically, we examine whether analysts' educational backgrounds affect the informativeness of their ratings.

Using hand-collected information on analysts' educational backgrounds, we find that when at least one analyst covering an ICO has an educational background in a related field (e.g., a computer science degree matches the blockchain infrastructure industry), the average rating is more informative in predicting the fundraising success of the ICO. Similarly, we show that analysts with advanced degrees also perform better. These analyst-level results help mitigate the endogeneity concerns regarding our baseline findings, which could be confounded by an unobservable ICO-level factor that is positively correlated with both headline analyst ratings and fundraising success.

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 analyst ratings spur aggressive early token subscriptions by outside investors. We find evidence that participants in a popular message board featuring cryptocurrencies and ICOs, BitcoinTalk.org, also pay close attention to analyst ratings.

We then 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, they are often hired as advisors in subsequent ICOs. According to Krawczyk (2019), an ICO advisor receives company tokens, the value of which ranges from $25,000 to $100,000, plus a cash retainer. In some cases, advisors also receive a portion of the gross proceeds that the company raises. In addition, advisors are typically offered investment

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

opportunities in the company. Analysts therefore can "make the big bucks" by serving multiple advisory roles.

We find that a one-percent increase in the number of ratings an analyst has issued is associated with a 3.3 to 3.9 percentage-point increase in the probability that the analyst holds advisory positions in the next three to six months. ICObench uses the number of ratings issued by an analyst as one major factor to determine her track record. Because the unconditional probability of serving as an advisor in our sample is 31.0%, the incremental probability of 3.3%-3.9% is economically meaningful. 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 whitepapers and other sources.

When ICObench produces the headline rating, ratings from analysts with good track records of producing high-quality ratings are more heavily weighted than the ratings from other analysts who cover the same ICO. Moreover, the rating with the highest weight is featured at 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 covers multiple ICOs. The intuition is similar to that employed by Masulis and Mobbs (2014), who find that a director with multiple directorships spends greater effort and time on the board that maximizes her visibility in the director labor market.

An analyst's relative rank in a given ICO is difficult to manipulate and therefore is less endogenous, as successful manipulation requires coordinating with all other analysts covering the ICO.[3] Using the 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

[3] For example, let us assume that an analyst covers two ICOs. She is the top-ranked analyst in the first ICO but ranked third in the second ICO. She has greater personal interest in the former token sale, which incentivizes her to exert greater effort to learn about the underlying project. Without the ability to control who else could cover the ICOs, the analyst cannot endogenize her relative rank in each of these ICOs.

likely to revise her rating if the covered ICO gives her the highest visibility. We further find that an individual rating becomes more informative in predicting fundraising success under the same condition. These results, taken together, suggest that more powerful reputational incentives induce analysts to exert more effort and produce more informative ratings.

Finally, we ask 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 find that analyst 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 analyst ratings also predict a lower probability of being delisted by major exchanges over various horizons.

In sum, we study how analyst expertise and incentives affect analysts' information-acquisition process, which appears to generate informative ratings indicating the quality of risky blockchain startups. In this respect, we make several contributions to the growing literature on ICOs.[4]

Our paper contributes to a growing body of literature on the economics of digital assets. We relate our findings to recent theoretical papers on ICOs, which include Cong et al. (2020), Gan et al. (2020), Lee and Parlour (2019), Li and Mann (2020), and Sockin and Xiong (2020). For example, our analysis of post-ICO token performance is related to Cong et al. (2020), who develop a dynamic asset-pricing model of tokens that features intertemporal feedback effects. Our study is also related to Howell et al. (2020), who examine which ICO characteristics predict employment and enterprise failure with an emphasis on the effect of token liquidity, while we focus on the expertise and incentives of online analysts rating ICOs. Bourveau et al. (2019) investigate information provision on ICOs, while we consider information aggregation by analysts.

Our study is also related to an emerging body of literature on the wisdom of crowds.

[4]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, e.g., Adhami et al. (2018), Fenu et al. (2018), Fisch (2019), and Momtaz (2018). On token underpricing, see, e.g., Benedetti and Kostovetsky (2018) and Dittmar and Wu (2019). On investor returns, see, e.g., Benedetti and Kostovetsky (2018), Dittmar and Wu (2019), Hu et al. (2019), and Lu (2018). On exchange listing, see, e.g., Amsden and Schweizer (2018), Lyandres et al. (2020), and Deng et al. (2018). On liquidity, see, e.g., Howell et al. (2020) and Lyandres et al. (2020). On GitHub activity, see Howell et al. (2020) and Deng et al. (2018). See Li and Mann (2019) and Ofir and Sadeh (2019) for a review of recent empirical studies on ICOs.

Chen, De, Hu and Hwang (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. Li (2018) provides a contracting solution to harness the wisdom of crowds in investment crowdfunding. Other studies in this area include Surowiecki (2005), Kovbasyuk (2011), Kremer, Mansour and Perry (2014), and Dindo and Massari (2017).

Another related area is the burgeoning literature on the economics of blockchain technology. Harvey (2016) discusses the mechanics of cryptofinance and their applications, 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 (2020) provides a formal economic model of the proof-of-stake blockchain protocol. For a broad overview on these recent developments on the blockchain economics, Allen et al. (2020) made an excellent survey on the literature.

Finally, our findings contribute to the ongoing discussion of ways to improve the design of crypto crowdfunding platforms. After experiencing a rapid rise in 2017-2018, the ICO market has begun to cool since late 2018, a development that is likely attributable to continued regulatory uncertainty and adverse cryptocurrency market conditions. 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.[5] Our documented market-based certification mechanism involving analysts might not fully resolve information asymmetry and governance problems in the blockchain crowdfunding market. However, analysts continue to cover alternative token sale methods such as STOs and IEOs. Understanding the role of ICO analysts is, therefore, useful for designing crowdfunding platforms that strive to achieve a higher level of informational efficiency.

[5]See Appendix I.1 and I.2 for additional details on the regulatory environment and evolution of token sales.

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 whitepaper, 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 whitepaper 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 Appendix II presents the timeline for a typical ICO.

2.2 Absence of traditional financial intermediation in the ICO market

ICOs differ radically from traditional corporate IPOs in that traditional financial intermediation is absent. With an IPO, investors exchange money for equity shares and voting rights in, typically, a relatively established company. In the U.S. and abroad, the process is underwritten by an investment bank and tightly regulated by securities regulators. To begin the IPO process, a firm is required to file a registration statement, which is a set of documents including a prospectus. After a "road show" to meet potential investors and gauge demand for the firm's stock, the underwriter "builds a book" by accepting orders from investors, who indicate the number of shares they desire and the price they are willing to pay. After the offer price is determined, the firm's management files a final prospectus with the regulatory authority and shares are allocated to investors. The issue is typically "closed" a few days later and shares begin their secondary market trading on a stock exchange. The underwriter also commits to making a liquid secondary market by assigning an analyst to cover the stock and, when necessary, it will step in to support the price.

In the freewheeling world of ICOs, however, none of these features exists. There is no investment bank to underwrite the token, conduct bookbuilding, or support secondary market trading. Token sales usually are open to investors around the world, regardless of where the startup is based. The vast majority of tokens are deemed utility tokens as opposed to securities or equity stakes. They typically lack voting rights and hence they confer no control. Compared with IPOs, ICOs are less transparent and subject to greater risk of fraud. In most cases, the startups issuing ICOs have no corporate track records or even products, although more established technology firms are increasingly using ICOs to fund their operations. Table A1 in Appendix II compares fundraising steps taken by ICOs and IPOs. In general, information asymmetry and governance challenges are keys to understanding ICOs.

2.3 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 non-blockchain-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 to analyst ratings, ICObench provides an algorithm-based rating (nicknamed the "Benchy" rating) ranging from 1 to 5 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, the algorithm considers only hard information in assessing an ICO, which is a primary distinction between Benchy ratings and analyst ratings.[6]

We use the headline rating immediately *before* an ICO starts, which is a weighted average of all analysts' ratings based on "expert scores."[7] ICObench assigns an expert score to each analyst, which takes into account all the ICOs they have 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.[8]

[6]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, among others. For product presentation, the algorithm checks the availability of such information through whitepapers, milestones, and video presentations. The algorithm also monitors activity on various social networks to determine whether an ICO team reaches potential investors.

[7]The reader is referred to https://icobench.com/ratings for a more detailed description of ICObench's rating methodology.

[8]Details regarding the expert score can be accessed via https://icobench.com/faq.

3 Sample Description

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 whitepapers, 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 whitepaper in multiple languages, and headline and individual ratings observed immediately before an ICO starts. We select ICOs that were completed by March 31, 2019 with non-missing key metrics mentioned above. Our main sample includes 3,392 completed ICOs, 811 of which were followed by token listings on cryptocurrency exchanges.

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 from all major exchanges and produces one standard price quote and trading volume.[9]

Analyst backgrounds

[9]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).

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.

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.

Potentially fraudulent ICOs

The U.S. Securities and Exchange Commission ("SEC"), the Commodity Futures Trading Commission ("CFTC"), and U.S. state securities 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 48 unique ICOs were charged by regulators.[10] 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 that were subject to enforcement actions, 41 exist in our sample. Another indicator of potential fraud is whether an ICO's whitepaper is downloadable. To avoid investor and regulatory scrutiny, scam ICOs often pull their whitepapers 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 whitepapers 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.

3.1 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.[11] 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.

[Insert Figure 1 here.]

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

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

[11] 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 (2018). After a successful fundraiser, it can take a startup 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.

in February 2018 before plummeting. The decline in total proceeds appeared to be closely 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.

[Insert Figure 2 here.]

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.[12] Combined, these token sales raised nearly $5.65 billion, accounting for 46.1% of all ICO proceeds raised during the same period. Table A2 in Appendix II shows the top 10 largest ICOs as of December 2018, with information on their fundraising periods and gross proceeds. In Table A3 in Appendix II we report the frequency of sales, fundraising success, and exchange listing rates for ICOs from each of the top 10 countries and industries.

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, there are also 72 engineers and technicians, who are potentially able to provide valuable insights into the technical aspects of ICOs. Other analysts represent 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.[13] All of the analysts who have either LinkedIn or Twitter accounts use their real names. Only one of these analysts uses two screen names on ICObench, one of which is genuine.

[12] 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.

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

[Insert Table 1 here.]

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 20% of the 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 LinkedIn nor Twitter accounts. 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 crowd-funding 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.

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 Appendix II Figure A2, we show similar patterns for hourly and block-level token subscriptions.

[Insert Figure 3 here.]

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) 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.

[Insert Table 2 here.]

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, 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.[14] 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.[15] 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 multi-language websites or whitepapers 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.[16] 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 shorter durations to completion (54 days), compared with 68 days for failed cases.

[14]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 give away control as voting rights typically are not attached to tokens.

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

[16]In contrast, according to the Crowdfunding Center, successful crowdfunding campaigns on average raised just $29,900 in 2016, 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).

4 Analyst Ratings and ICO Outcomes

4.1 Analyst ratings and ICO success

In Table 3, Panel A we report the results of predictive regressions where the dependent variables are proxies for ICO success. For column (1), the dependent variable is ICO 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).[17] For columns (2) and (3), we replace the dependent variable with the exchange listing dummy and gross proceeds, respectively. The main independent variables are the same as the ICO characteristics presented in our summary Table 2, with the critical difference that all variables in the regressions are measured at the time of an ICO announcement. For ease of interpretation, we report coefficients derived from a linear probability model with country, industry, and quarter fixed effects. Table A4 in Appendix II further displays the probit coefficients and their associated marginal probabilities. The results are qualitatively similar.

[Insert Table 3 here.]

We find that, all else being equal, the average analyst 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 average rating is associated with an increase in the marginal probability of 13.1 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 these experts play in a market that lacks traditional underwriters. In robustness analysis, we exclude ratings from experts who are connected to company insiders via prior projects and therefore could be biased. We obtain results that are virtually unchanged.

The coefficients associated with three additional ICO characteristics are worth further noting. With each one-standard-deviation increase in the fraction of tokens for sale, there is a 5.1 percentage-point decrease in the marginal probability of ICO success (a finding that is significant at the 1% level). This is consistent with managerial incentive signaling as theorized by Leland and Pyle (1977) and Downes and Heinkel (1982). Token sales providing large bonuses are 4.0 percentage-points less likely to successfully conclude, reflecting investor rationing to

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

ICOs with overly generous bonuses, many of which are believed to be potential scams (Sagar, 2017). Including a presale can boost the likelihood of success by 4.0 percentage points (a finding that is significant at the 5% level), suggesting that successful initial sales can promote subsequent token sales.

For other characteristics, we obtain results that are similar to our sample statistics on successful versus failed ICOs; the customer identification requirement is insignificant, while multi-language websites/whitepapers, multiple currencies, and token sales classified as STOs are significantly more likely to succeed.[18]

As shown in column (2), our results are qualitatively similar when replacing the fundraising success dummy with the exchange-listing indicator. As seen in column (3), we replace the dependent variable with the logarithm of gross proceeds to reflect the degree of fundraising success, we obtain similar results; gross proceeds increase by 75% when the average analyst rating increases by one point.[19] In Appendix II Table A5, we show that favorable analyst ratings are also associated with a quicker token sale, all else equal.

As an additional robustness check, we examine whether key ICO attributes and market conditions explain analyst ratings, and test whether the ratings have any incremental explanatory power for funding success even after we take this possibility into account. We report the results in Appendix II Table A6 that are largely consistent with our earlier findings. It is worth noting that higher governance quality, such as more skin in the game and KYC policies, positively predicts rating levels, while crypto-market returns or price levels during the previous quarter or month do not affect ratings on average.

4.2 Analyst ratings and 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 expert ratings are also useful for predicting fraudulence in ICOs. In Appendix I.3, we provide an example of a genuine ICO and another example of a fraudulent token sale.

[18] Securities regulators have made it difficult, however, for cryptocurrency exchanges to list STOs, which is not an issue for utility tokens. In 2018, the only secondary markets available to STOs were decentralized exchanges, which generally are less illiquid.

[19] Our test sample in this regression is smaller as the analysis requires specific information on gross proceeds and/or hard caps.

ICOs with missing whitepapers

Our first proxy for potential fraud is whether an ICO removes its whitepaper. To go dark without leaving a trace, fraudulent ICOs often pull their whitepapers 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 analyst rating as the ratings are issued prior to the token sales. We examine the characteristics of the 262 ICOs that removed their whitepapers. As shown in column (1) of Table 3, Panel B, analysts ex ante issue a significantly lower rating for ICOs with missing whitepapers. These ICOs also exhibit lower governance quality—the insiders have less skin in the game and they tend to offer more generous bonuses. The token sales are also less likely to feature multi-language websites. In Appendix II Table A8, Panel A, we show evidence that ICOs missing whitepapers have a significantly lower fundraising success rate, raise less funds, and are less likely to be listed.

ICOs charged by regulators

Although ICOs that pulled whitepapers are more likely to be fraudulent, it is difficult to ascertain that they must be scams. We thus repeat our analysis using ICOs that involved ex-post fraud charges by U.S. regulators, such as AriseBank and Centra Tech. In column (2) of Table 3, Panel B, we report that analysts ex ante assign a lower rating to charged ICOs. Moreover, the fraudulent ICOs are less likely to require a KYC procedure and the insiders retain fewer tokens. In Appendix II Table A8, 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.

Overall, in Panel B of Table 3, 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.

4.3 Analyst ratings and primary market subscriptions

Now we go one step further to see how good analyst 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 analyst ratings are correlated with such differences in primary market subscription patterns, we use the following regression:

$$Subscription_{kijt} = \alpha + \beta Rating_{kijt} + \delta X_{kijt} + \lambda_t + \rho_i + \mu_j + \epsilon_{kijt}, \tag{1}$$

in which $Subscription_{kijt}$ represents measures that gauge primary market subscriptions for token sale k that starts in quarter t in industry i and country j. $Rating_{kijt}$ is the average analyst rating measured *immediately before* token sale k starts in quarter t. X_{kijt} is a vector representing ICO-level covariates. λ_t represent quarter fixed effects, and ρ_i and μ_j are industry and country fixed effects, respectively. ϵ_{kijt} is the error term. Standard errors are clustered along the quarter dimension. This is a purely cross-sectional analysis.

As reported in column (1) of Table 4, the average analyst 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 average analyst rating and the aggressive first-day subscriptions are correlated with the latent ICO quality factors, the pre-determined analyst rating variable is not subject to any reverse causality. A one-standard-deviation increase in the average rating is associated with an increase in first-day tokens sold of 2.2 percentage points (a finding that is significant at the 5% level). This suggests that positive analyst ratings help harness 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 analyst ratings also strongly predict token sales during the first five and 15 days of an ICO, respectively.

[Insert Table 4 here.]

5 Analyst Ratings and Investor Attention

To understand how analyst ratings affect success of ICOs, it is useful to understand whether analyst ratings influence investors' attention to the underlying projects. Data on investor attention to the analyst ratings are not available. We instead construct a proxy for investor attention based on message board activities on Bitcointalk.org.

BitcoinTalk.org is the one of the most popular 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, whitepaper, 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. For each of these ICOs, we download the announcement, posts, and their respective timestamps.

[Insert Table 5 here.]

We measure potential investors' response to the rating by counting the numbers of posts during the seven-day window before and after an individual analyst 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. In column (1) of Table 5, we find that the growth rate in BitcoinTalk posts is sensitive to individual analyst's rating. If there are more than one rating issued on a given day, we take the average of them. In all regressions, we include *Days elapsed since first rating* that is the number of days elapsed since the first rating for an ICO was issued in order to control for the timing of issuance of rating. The effect is statistically and economically significant. One-standard-deviation increase in analyst ratings 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 fixed effect and ICO fixed effect as shown in column (2) and (3). In the untabulated results, we find that results are robust even if we shorten the event window to a five-day window around the analyst rating announcement.

As mentioned in Section 2.3, ICObench assigns a weight to each analyst who rates an ICO, based on their expert scores. In column (4), (5) and (6), we include *Highest weight* and its interaction with *Individual analyst rating*, where *Highest weight* is a dummy that equals 1 if a rating is issued by an analyst with the highest weight in the ICO. If there is more than one rating, *Highest weight* is equal to 1 if at least one of them is such analyst with the highest weight. We observe that the investors' response to the rating is more sensitive if the rating is issued by an analyst with the highest weight, which suggests that investors might tend to care more about ratings by analysts whose weights are high in the ICObench platform. Furthermore, as the temporal reaction by potential investors is not influenced by any constant ICO-level confounders, this result also helps alleviate omitted variable concerns to a certain extent.[20]

[20] We note, however, that not every participant on BitcoinTalk may be an actual investor in a given ICO.

Overall, while the results are not conclusive, they collectively suggest that potential investors appear to pay attention to analyst ratings.

6 Analyst Backgrounds and ICO Success

Analyst ratings positively predict fundraising success, which suggests that on average, ratings reveal useful information for investors when they make ICO investment decisions. To provide informative ratings, analysts are expected to have a deep understanding of the underlying technologies such as blockchain, mining, and cryptography. We posit that analysts who have a technical background are more likely to understand the important issues associated with an ICO and generate more useful insights for investors. It is therefore of interest to examine whether analysts' educational backgrounds affect the informativeness of their ratings.[21] This conditional test is also important from an identification point of view because we introduce an additional variation in analyst characteristics and test whether they predict any stronger association between analyst ratings and ICO success. This result is less prone to the ICO-level confounders by design, which further alleviates the omitted variable concerns.

We consider both terminal degrees in science/technology and/or business/economics-related fields. We also consider advanced degrees in any discipline (master's/PhD) as being useful to informed ICO analysts. As shown in column (1) of Table 6, we find that when at least one analyst covering an ICO has an educational background in a related field to the given ICO (e.g., a computer science degree matches the blockchain infrastructure industry), their average rating is more informative in predicting the successful fundraising. In columns (2) and (4), the reported results further show that when analysts possess science/technology degrees or any advanced degrees, an ICO is significantly more likely to conclude successfully. Analysts possessing terminal science/technology degrees or advanced degrees could leverage their specialized knowledge to better assess future values for blockchain-related companies. Our findings are consistent with those of Klein et al. (2020), who find that sell-side equity analysts with advanced degrees in science or medicine make more profitable recommendations on healthcare stocks. Bradley et al. (2017) also document similar results such that equity analysts with relevant work experience in their covered industries perform much better in forecasting earnings. We extend their findings

The number of posts on this representative online forum serves as a proxy for investor attention and interest.

[21] In ongoing work, we are analyzing how previous industry experience affects the performance of an analyst's ratings.

to ICO analysts, which has not been documented in the nascent ICO literature.

[Insert Table 6 here.]

In column (3), we report results based on whether analysts have earned business or economics degrees and find that such degrees have little effect on ICO fundraising success.[22]

7 Analyst Incentives and ICO Success

7.1 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 et al., 2016; Kempf, 2020),[23] 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 the later launched 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 advisor at least once, the average analyst in our sample has occupied 7.1 advisory positions in total.

According to Krawczyk (2019)[24], 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.[25]

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

[22] De Franco and Zhou (2009) also find relatively weak evidence that having a CFA improves an equity analyst's ability to forecast earnings. Klein et al. (2020) find found similar results as well.

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

[24] ICO Advisor Compensation for 2019: https://medium.com/@TheMrBlueprint/ico-advisor-compensation-for-2019-6f6b31bcc77c

[25] 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: https://medium.com/@TheMrBlueprint/ico-advisor-compensation-for-2019-6f6b31bcc77c).

an analyst has issued in the past or in the past three months. We also use "top 10 expert," a monthly designation awarded by ICObench based on analysts' track records, as another measure of analyst reputation.

Table 7, Panel A, reports the results. A one-percent increase in the number of ratings an analyst has issued is associated with a 3.3 to 3.9 percentage-point increase in the probability that the analyst holds advisory positions in the next three to six months. Given that the unconditional probability of serving as an advisor is 31.0%, the incremental probability is economically significant. 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.

[Insert Table 7 here.]

In Panel B, we repeat our analysis by replacing the dependent variable with the natural logarithm of the number of advisory positions that an analyst holds in the three to six months following a rating issuance. Our results are largely unchanged; analyst reputation helps obtain lucrative advisory positions in the later ICO projects, enhancing the analysts' careers in this business community.[26]

7.2 Platform-Driven Incentives

We conduct a few additional analyses to examine 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 (Masulis and Mobbs, 2014). In the board of directors literature, Masulis and Mobbs (2014) 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 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 given

[26]In Appendix Table A7, 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.

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.[27] His rating has a weight of 10%, the highest among the 12 ratings.[28] Importantly, in other ICOs, the same analyst is ranked differently depending on his expert score relative to those of other analysts. This indicates that the same analyst's visibility varies across ICOs.

[Insert Figure 4 here.]

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 for a given analyst, controlling for the analyst's individual fixed effect or analyst-quarter fixed effects. The relative rank of an analyst in a given ICO is difficult to manipulate, and thus, is plausibly exogenous.

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 8, Panel A, we regress a dummy variable, *Revision*, an indicator for the analyst to revise her rating, on *ICO with highest visibility*, a dummy indicating whether the given ICO provides the highest visibility to the analyst. Column (1) shows that an analyst is 4.2 percentage-point 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 analysts who issue multiple ratings in a given quarter. We obtain similar results.

[Insert Table 8 here.]

In Panel B, we proceed by regressing fundraising success of an ICO on the interaction between an individual analyst's rating and the *ICO with highest visibility* dummy. We use the most recent rating before an ICO starts. In addition to ICO-level controls, we also control for analyst fixed effects or analyst-quarter fixed effects. As shown in Panel B of Table 8,

[27]See Section 2.3 for more details on ICObench's expert score system.

[28]Owing to 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.

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 they provide.[29]

8 Post-ICO Performance

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

8.1 Long-run performance

In Table 9, we summarize token returns for various horizons. Starting with the six-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 six-month excess return is highly positive at 45%. These statistics indicate that token returns over this relatively long horizon are highly skewed. For the one-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 Benedetti and Kostovetsky (2018). When using the top 10 digital currencies' value-weighted return as an alternative market benchmark, we obtain similar results.[30]

[Insert Table 9 here.]

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

[29]One concern regarding the analysis in Table 8, Panel B is whether the analyst with the highest visibility knows when issuing the rating that she will eventually be most visible in the ICO. We discuss this timing issue in depth in Appendix I.4.

[30]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 one-year returns than of returns over shorter horizons. As we gather more observations of token returns, we plan to analyze their longer-term performance in the future.

three-month, six-month, and one-year total returns as the dependent variables. In addition to analyst 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 run 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).

[Insert Table 10 here.]

For all three horizons, long-run returns are inversely related to initial returns, exhibiting potential mean reversions. Most importantly, we find that a good average analyst rating significantly predicts positive returns over the three horizons. Both the economic and statistical significance is greatest for the one-year horizon. For example, a one-point increase in the average rating is associated with an 8.7 percentage-point increase in one-year returns, all else being equal. Recall that analyst ratings focus on team, vision, and product, all of which are long-term indicators of underlying startup quality. This implies that analyst 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 analyst 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.

8.2 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 $\sqrt{365}$ to obtain returns for the three-, six-, and 12-month periods after a token is listed. Listed tokens trade 365 days a year.

As shown in Table 11, more favorable analyst ratings are associated with lower token return volatility over the three-, six- and 12-month horizons, all else remaining equal. More stable token prices increase tokens' desirability as a medium of exchange on platforms. Higher analyst 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.

[Insert Table 11 here.]

9 Conclusion

This is the first study that examines whether and how online analysts help mitigate information asymmetry in fundraising campaigns that lack financial intermediation. We find that favorable analyst ratings for blockchain-based projects are associated with aggressive initial token subscriptions by investors and eventual fundraising success. We also show that favorable analyst ratings boost investor attention and predict positive post-offering token performance over long horizons.

Importantly, we find that analysts with technical backgrounds or advanced degrees tend to issue more informed ratings. Relatedly, those recognized as top analysts by the crypto community are more likely to be hired as advisors in future ICOs. This career incentive is found to lead to more informative ratings. We also examine how platform-specific visibility incentives induce more informative ratings by online ICO analysts.

In addition to predicting fundraising success, analyst ratings predict potential ICO 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. We show that their expertise and incentives matter in this emerging alternative financing model.

Although we provide supporting evidence for market-based certification by ICO analysts, this analyst-based certification alone may not be able to fully resolve all the remaining governance issues in this market. Given their market's "Wild-West" nature, ICOs will continue to evolve to take the next generation of forms, where several additional features could be added to the platform to further mitigate residual information asymmetry and governance problems (e.g., a rush of IEOs). Our aim in future research is to explore such features from the optimal platform design perspective, which is essential to sustain the crypto-based funding market without resorting to traditional financial intermediaries.

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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.

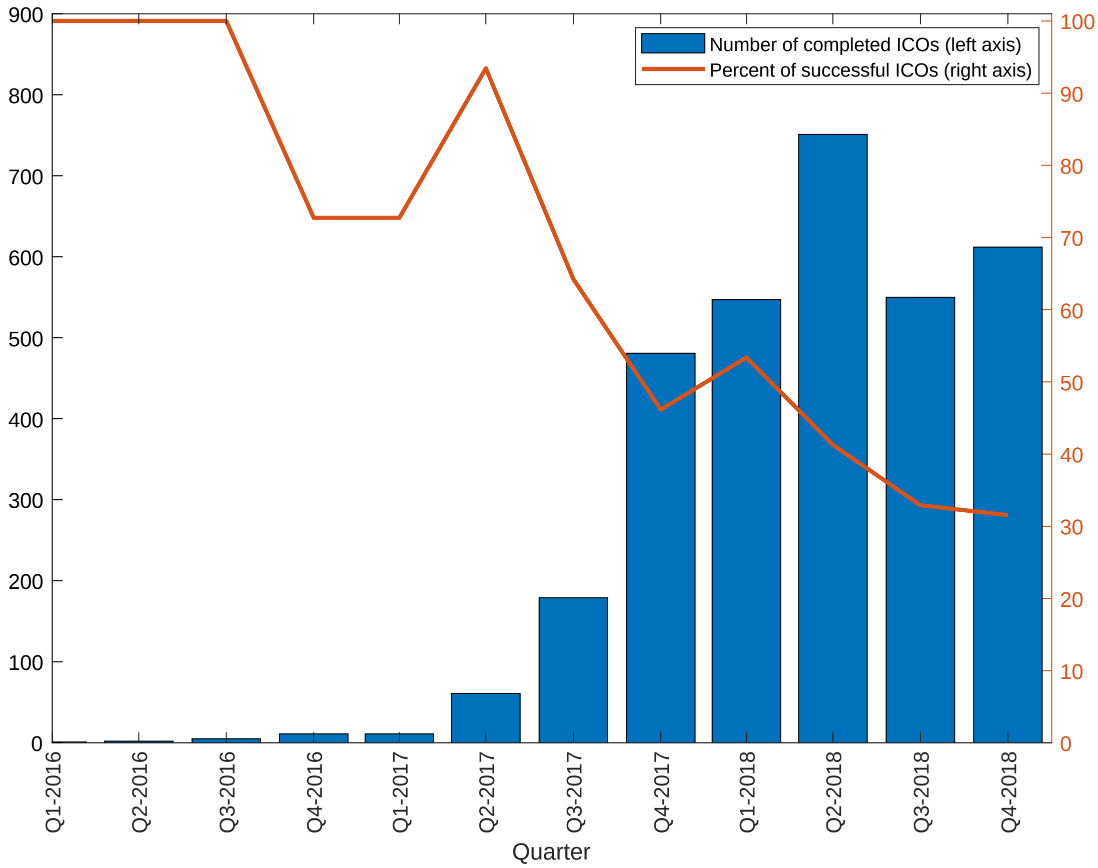


Figure 2: Total Gross Proceeds and Bitcoin Price

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.

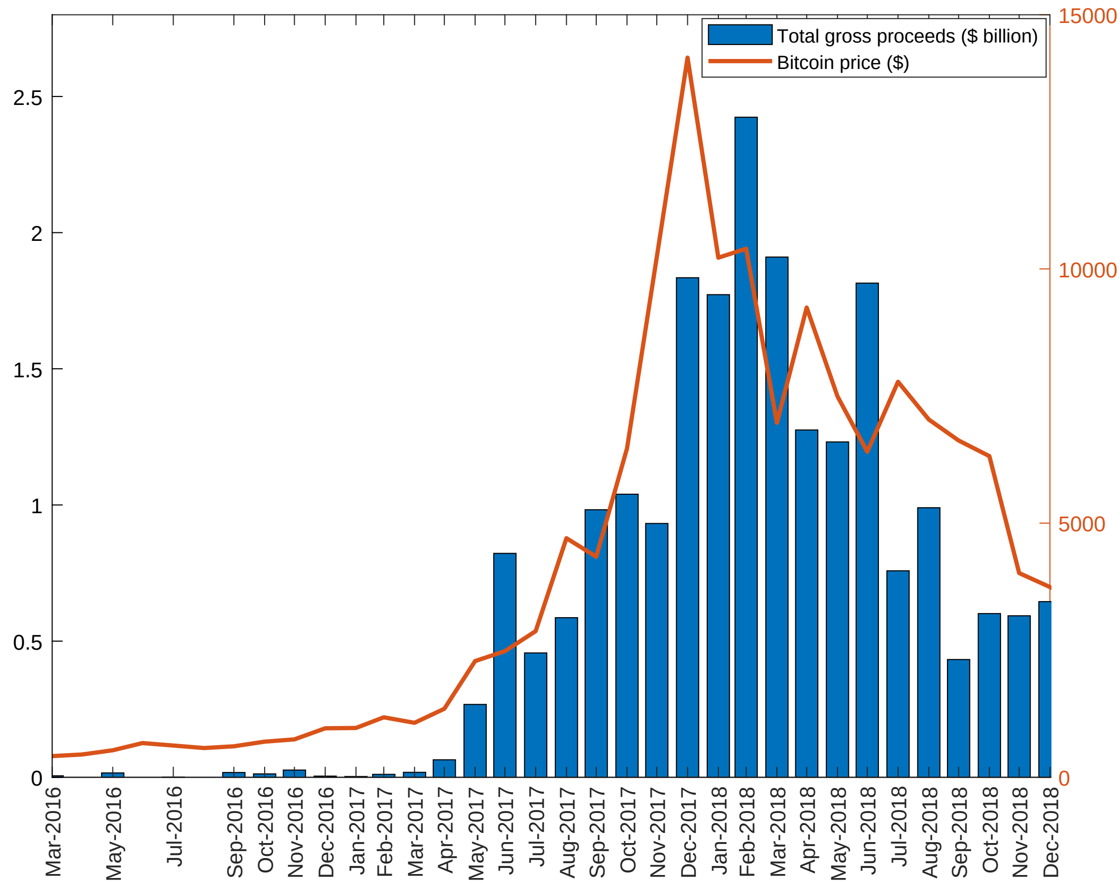


Figure 3: Primary Market Subscriptions in ICOs

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.

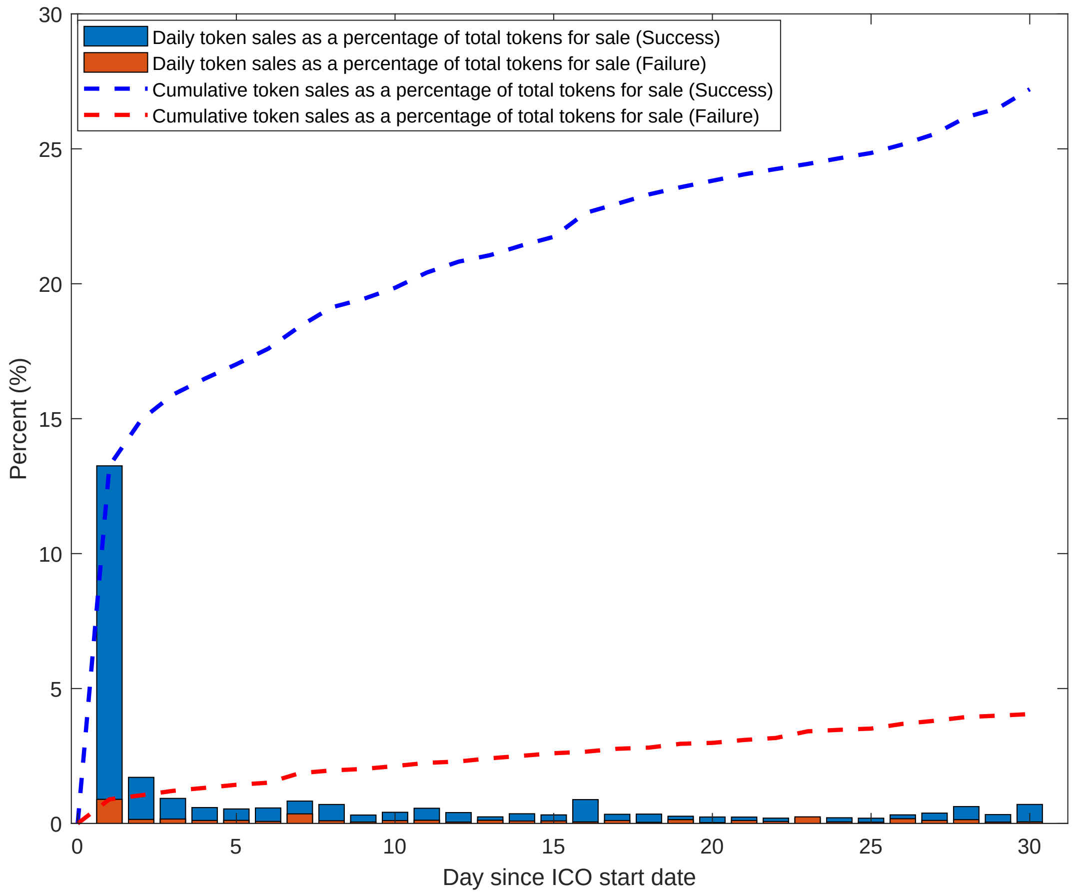
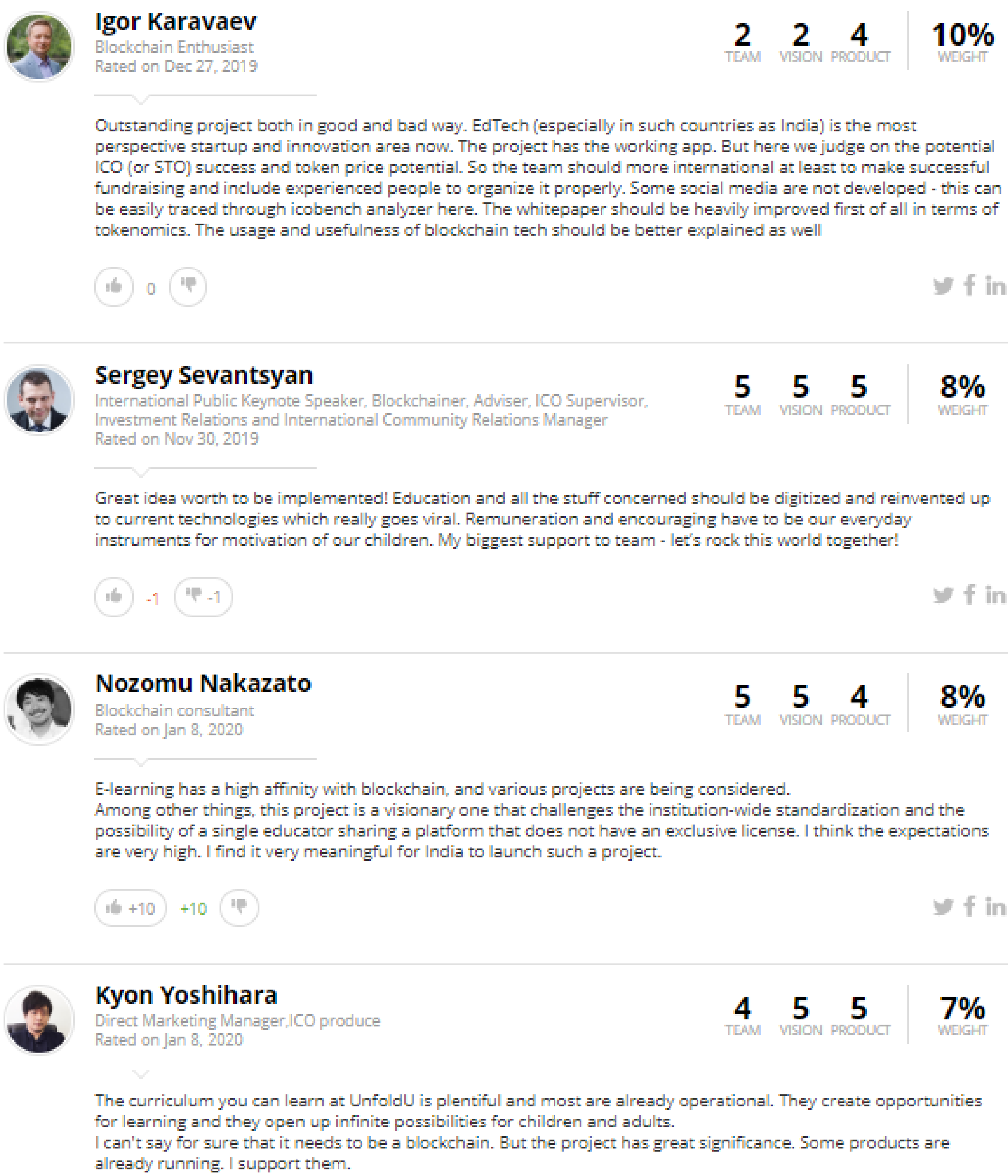


Figure 4: Visibility of Analysts in an ICO

This figure shows the analyst 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.



Igor Karavaev
Blockchain Enthusiast
Rated on Dec 27, 2019

2 TEAM 2 VISION 4 PRODUCT 10% WEIGHT

Outstanding project both in good and bad way. EdTech (especially in such countries as India) is the most perspective startup and innovation area now. The project has the working app. But here we judge on the potential ICO (or STO) success and token price potential. So the team should more international at least to make successful fundraising and include experienced people to organize it properly. Some social media are not developed - this can be easily traced through icobench analyzer here. The whitepaper should be heavily improved first of all in terms of tokenomics. The usage and usefulness of blockchain tech should be better explained as well

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Sergey Sevantsyan
International Public Keynote Speaker, Blockchainer, Adviser, ICO Supervisor, Investment Relations and International Community Relations Manager
Rated on Nov 30, 2019

5 TEAM 5 VISION 5 PRODUCT 8% WEIGHT

Great idea worth to be implemented! Education and all the stuff concerned should be digitized and reinvented up to current technologies which really goes viral. Remuneration and encouraging have to be our everyday instruments for motivation of our children. My biggest support to team - let's rock this world together!

-1 -1

Nozomu Nakazato
Blockchain consultant
Rated on Jan 8, 2020

5 TEAM 5 VISION 4 PRODUCT 8% WEIGHT

E-learning has a high affinity with blockchain, and various projects are being considered.
Among other things, this project is a visionary one that challenges the institution-wide standardization and the possibility of a single educator sharing a platform that does not have an exclusive license. I think the expectations are very high. I find it very meaningful for India to launch such a project.

+10 +10

Kyon Yoshihara
Direct Marketing Manager,ICO produce
Rated on Jan 8, 2020

4 TEAM 5 VISION 5 PRODUCT 7% WEIGHT

The curriculum you can learn at UnfoldU is plentiful and most are already operational. They create opportunities for learning and they open up infinite possibilities for children and adults.
I can't say for sure that it needs to be a blockchain. But the project has great significance. Some products are already running. I support them.

Table 1: Analysts' Characteristics

In this table, we report characteristics of the 497 online analysts that covered our sample ICOs. *Active LinkedIn page* is an indicator that equals 1 if an analyst has an active LinkedIn page. *# LinkedIn connections > 500* is a dummy variable that equals 1 if an analyst has more than 500 connections on LinkedIn. *Science/Tech degree* equals 1 if an analyst holds a university degree in science or technology and 0 otherwise. *Business/Economics degree* equals 1 if an analyst holds a university degree in business- or economics-related degree and 0 otherwise. *master's/PhD degree* equals 1 if an analyst holds a Master's or PhD degree in any discipline and 0 otherwise. *Times top 100 university* is an indicator equal to 1 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 1 if an analyst does not disclose any educational background on their LinkedIn page and 0 otherwise. *Active Twitter account* is an indicator that equals 1 if an analyst has an active Twitter account and 0 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, the number of people the analyst follows, respectively. *No LinkedIn or Twitter account* is a dummy variable that equals to 1 if an analyst has neither active LinkedIn nor Twitter accounts and 0 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 1 if an analyst is ranked among top 10 experts at least once during our sample period and 0 otherwise.

	Average	25th Percentile	Median	75th Percentile	Std. Dev.	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

Table 2: ICO Characteristics

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. *Analyst 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 1 if an ICO runs a token sale event before the official crowdsale goes live and 0 otherwise. *High bonus* equals 1 if an ICO offers a bonus of over 20% (equivalent to a discount of 16.7%) and 0 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 1 if clients are required to provide information to confirm their identities and 0 otherwise. *Whitelist* is a dummy variable that equals 1 if customers have to register in advance to participate in an ICO and 0 otherwise. *Participation restriction* equals 1 if an ICO is restricted in certain countries and 0 otherwise. *Multiple languages* is an indicator that equals 1 if the whitepaper or website for an ICO features more than one language and 0 otherwise. *Multiple currencies* equals 1 if an ICO accepts multiple currencies (digital or fiat) and 0 otherwise. *STO* is an indicator that equals 1 if an ICO offers tokens with features comparable to securities that are regulated in at least one jurisdiction and 0 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.

	Successful ICOs			Difference between successful and failed ICOs		
	Average	Median	Std. Dev.	Diff. in Avg.	t-stat of Diff.	Wilcoxon
	(1)	(2)	(3)	(4)	(5)	(6)
Ex ante ICO characteristics						
Analyst 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

Table 3: Analyst Ratings and ICO Outcomes

In Panel A, we report results pertaining to the determinants of fundraising success and exchange listing for all ICOs that started between January 1, 2016 and December 31, 2018 and were completed as of March 31, 2019. Of our sample ICOs, 811 were listed on at least one exchange. *Fundraising success* is an indicator that equals 1 if an ICO reaches its soft cap or the project raises more than $0.5 million in the absence of a soft cap and 0 otherwise. *Exchange listing* is a dummy variable that equals 1 if tokens issued in an ICO was listed on an exchange during our sample period and 0 otherwise. *Log(Gross proceeds)* is the logarithm of gross proceeds in millions of dollars. Our sample is reduced to 1,915 ICOs for which we find specific information on gross proceeds. In Panel B, we report results pertaining to the determinants of potentially fraudulent ICOs. *Missing whitepaper* is an indicator that equals 1 if an ICO does not have a downloadable whitepaper and 0 otherwise. *Charged by regulators* is a dummy variable that equals 1 if an ICO is charged by U.S. regulators. All independent variables are as defined in Table 2 and are measured immediately before ICO start dates. In each column we report coefficient estimates and their t-statistics. Standard errors are clustered at the quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. ICO success

Dependent variable:	Fundraising success (1)	Exchange listing (2)	Log(Gross proceeds) (3)
Analyst rating	0.167***	0.140***	0.752***
	[8.53]	[4.84]	[8.50]
No. of analysts	0.008***	0.005***	0.010**
	[4.03]	[2.92]	[2.02]
Fraction of tokens for sale	-0.251***	-0.188***	-0.851***
	[-9.18]	[-4.25]	[-2.99]
Presale	0.040**	0.020	0.027
	[2.22]	[1.35]	[0.25]
High bonus	-0.040***	-0.049***	-0.371***
	[-3.34]	[-3.99]	[-3.22]
Know Your Customer	-0.012	-0.023	-0.028
	[-0.89]	[-1.41]	[-0.22]
Multiple languages	0.067***	0.077***	0.211**
	[4.73]	[2.58]	[2.37]
Multiple currencies	0.029*	0.018**	0.486
	[1.83]	[1.97]	[5.10]
STO	0.155**	-0.057	0.189
	[2.12]	[-0.97]	[0.77]
Quarterly fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Observations	3,392	3,392	1,915
Adj. R-squared	0.23	0.32	0.02
% (Dep variable = 1)	42.4%	23.9%	N/A

Panel B. Potentially fraudulent ICOs

Dependent variable:	Missing whitepaper (1)	Charged by regulators (2)
Analyst rating	-0.034***	-0.006*
	[-3.07]	[-1.93]
No. of analysts	0.001	0.0002
	[1.41]	[0.31]
Fraction of tokens for sale	0.049**	0.009*
	[2.26]	[1.74]
Presale	-0.024***	0.005
	[-3.40]	[1.40]
High bonus	0.006*	-0.004
	[1.94]	[-1.36]
Know Your Customer	0.009	-0.011**
	[1.20]	[-2.37]
Multiple languages	-0.033***	0.001
	[-3.66]	[0.44]
Multiple currencies	-0.005	0.006
	[-1.09]	[1.62]
STO	-0.008	0.017
	[-0.33]	[1.27]
Quarterly fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Observations	3,392	3,392
Adj. R-squared	0.07	0.02
% (Dep variable = 1)	7.7%	1.2%

Table 4: Analyst Ratings and Primary Market Token Subscriptions
In this table, we report results indicating how analyst 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, and are measured immediately before ICO start dates. In each column we report coefficient estimates and their t-statistics. Standard errors are clustered at the quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	First-day subscription (1)	Subscription b/t 1^{st} and 5^{th} days (2)	Subscription b/t 1^{st} and 15^{th} days (3)
Analyst rating	0.029**	0.039***	0.049***
	[2.49]	[2.61]	[3.54]
No. of analysts	0.001**	0.001***	0.001**
	[1.96]	[2.66]	[2.15]
Fraction of tokens for sale	-0.047*	-0.064	-0.083**
	[-1.90]	[-1.64]	[-2.34]
Presale	-0.009*	-0.016***	-0.014***
	[-1.85]	[-2.91]	[-2.90]
High bonus	-0.017***	-0.022***	-0.026***
	[-3.76]	[-3.49]	[-4.04]
Know Your Customer	-0.010	-0.010	-0.014
	[-1.15]	[-0.87]	[-1.12]
Multiple languages	0.005	0.004	-0.001
	[0.49]	[0.29]	[-0.07]
Multiple currencies	-0.007	-0.011**	-0.006
	[-1.10]	[-2.08]	[-1.10]
STO	0.027	0.025	0.022
	[0.92]	[0.88]	[0.79]
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	0.12	0.11	0.13

Table 5: Analyst Ratings and Investor Attention

In this table, we report results indicating whether analyst ratings affect investor attention by merging the data from ICObench and Bitcointalk.org. *Individual analyst rating* is the individual analyst rating on a given day. If there are more than one rating on a given day, we take the average of them. *Highest weight* is a dummy variable that equals 1 if the rating is issued by an analyst who has the highest weight in an ICO and 0 otherwise. If there are more than one rating on a given day, this variable equals 1 if one of the ratings is issued by an analyst with the highest weight. *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 0. *Log growth rate of # of posts with 7-day window* is logarithm of 1 + the number of posts during the seven-day window after the rating is issued divided by the number of posts during the seven-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. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	Log growth rate of # of posts with 7-day window					
	(1)	(2)	(3)	(4)	(5)	(6)
Individual analyst rating	0.036***	0.038***	0.026***	0.025***	0.028***	0.020**
	[5.21]	[5.54]	[3.39]	[3.02]	[3.48]	[2.25]
Highest weight				-0.148***	-0.123***	-0.084
				[-2.92]	[-2.41]	[-1.58]
Highest weight ×Individual analyst rating				0.037***	0.032**	0.024*
				[2.83]	[2.44]	[1.75]
Days elapsed since first rating	-0.00018***	-0.00006	-0.00162*	-0.00018***	-0.00006	-0.00162*
	[-2.69]	[-0.93]	[-1.76]	[-2.68]	[-0.93]	[-1.77]
Month fixed effects	No	Yes	No	No	Yes	No
ICO fixed effects	No	No	Yes	No	No	Yes
Observations	8,792	8,792	8,386	8,792	8,792	8,386
Adj. R-squared	0.005	0.015	0.118	0.006	0.016	0.118

Table 6: Analyst Backgrounds and ICO Success

This table relates analyst educational backgrounds with 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 1 if an ICO reaches its soft cap or the project raises more than $0.5 million in the absence of a soft cap and 0 otherwise. *Degree matches ICO industry* is a dummy variable equal to 1 if among the analysts covering an ICO, at least one analyst's area of study matches the ICO industry broadly (e.g. a computer science degree matches the blockchain infrastructure industry) and 0 otherwise. *Science/Tech degree* if at least one analyst covering an ICO holds a university degree in science or technology and 0 otherwise. *Business/Economics degree* equals 1 if an analyst holds a business- or economics-related degree and 0 otherwise. *Master's/PhD degree* equals 1 if at least one analyst covering an ICO holds a Master's or PhD degree in any discipline and 0 otherwise. All other independent variables are as defined in Table 2 and are measured immediately before ICO start dates. In each column we report coefficient estimates and their t-statistics. Standard errors are clustered at the quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Fundraising success			
	(1)	(2)	(3)	(4)
Analyst rating	0.173***	0.151***	0.160***	0.155***
	[8.71]	[9.47]	[6.70]	[6.41]
Analyst rating × Degree matches ICO industry	0.035**			
	[2.20]			
Degree matches ICO industry	-0.028			
	[-0.45]			
Analyst rating × Science/Tech degree		0.047***		
		[2.90]		
Science/Tech degree		-0.045		
		[-0.78]		
Analyst rating × Business/Economics degree			0.032	
			[1.48]	
Business/Economics degree			-0.009	
			[-0.12]	
Analyst rating × Master's/PhD degree				0.047**
				[1.98]
Master's/PhD degree				-0.064
				[-0.74]
Fraction of tokens for sale	-0.251***	-0.254***	-0.250***	-0.251***
	[-8.11]	[-8.45]	[-8.16]	[-8.41]
Presale	0.038*	0.039**	0.040**	0.040**
	[2.15]	[2.36]	[2.27]	[2.47]
High bonus	-0.039***	-0.038***	-0.038***	-0.038**
	[-3.40]	[-3.08]	[-3.22]	[-2.95]
Know Your Customer	-0.013	-0.015	-0.015	-0.015
	[-0.93]	[-1.03]	[-1.11]	[-1.09]
Multiple languages	0.078***	0.076***	0.074***	0.074***
	[5.31]	[5.31]	[5.25]	[5.35]
Multiple currencies	0.031	0.027	0.029	0.027
	[1.63]	[1.52]	[1.62]	[1.48]
STO	0.143*	0.154**	0.145**	0.149**
	[1.84]	[1.98]	[2.02]	[2.05]
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	0.22	0.32	0.22	0.22
% (Dep variable = 1)	42.4%	42.4%	42.4%	42.4%

Table 7: Analyst Career Incentives

This table relates analyst experience and reputation with advisory roles in future ICOs. *Log(#Ratings issued)* is the logarithm of the number of ratings issued by an analyst in the past. *Log(# Ratings issued in past 3 months)* is the logarithm of the number of ratings issued by an analyst in the past three months. *Top 10 expert* is a dummy variable that equals 1 if an analyst is ranked among the top 10 experts by ICObench in a given month and 0 otherwise. *Holds advisory positions in months [+3, +6]* equals 1 if an analyst holds at least one ICO advisory position between 3 and 6 months after a given month, and 0 otherwise. *Log(1+#ICO advisory positions held in months [+3, +6])* is the logarithm of 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 month level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel 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 controls	No	Yes	No	Yes	No	Yes
Observations	2,596	2,544	2,596	2,544	2,596	2,544
Adj. R-squared	0.04	0.16	0.09	0.19	0.07	0.18

Panel B. Number of ICO advisory positions

Dependent variable:	Log(1+#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 controls	No	Yes	No	Yes	No	Yes
Observations	2,596	2,544	2,596	2,544	2,596	2,544
Adj. R-squared	0.03	0.17	0.07	0.19	0.06	0.18

Table 8: Platform-Driven Incentives of Individual Analysts

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 to 1 if an analyst revised his/her rating and 0 otherwise. *Fundraising success* is an indicator that equals 1 if an ICO reaches its soft cap or the project raises more than \$0.5 million in the absence of a soft cap and 0 otherwise. *ICO with highest visibility* is a dummy variable that equals 1 if an ICO gives an analyst the highest visibility among all analysts who cover the ICO because his/her weight is the highest among them and 0 otherwise. If there are more than one person who has the highest weight, we give all of them 1. *Individual analyst rating* is an individual analyst's rating for an ICO. All other ICO level variables are as defined in Table 2, and are measured immediately before ICO start dates. In each column we report coefficient estimates and their t-statistics. Standard errors are clustered at the analyst×quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Highest visibility and revision of ratings

Dependent variable:	Revision	
	(1)	(2)
ICO with highest visibility	0.042***	0.039***
	[3.78]	[3.43]
No. of analysts	0.0003	0.0003
	[1.31]	[1.17]
Fraction of tokens for sale	0.004	-0.006
	[0.27]	[-0.41]
Presale	-0.005	-0.001
	[-0.61]	[-0.16]
High bonus	0.008	0.008
	[0.79]	[1.17]
Know Your Customer	-0.003	-0.010
	[-0.55]	[-1.62]
Multiple languages	0.005	0.004
	[1.01]	[1.22]
Multiple currencies	-0.014**	-0.015***
	[-2.40]	[-2.68]
STO	0.007	0.015
	[0.55]	[0.90]
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	0.24	0.28
% (Dep variable = 1)	9.4%	9.4%

Panel B. Highest visibility and informativeness of ratings

Dependent variable:	Fundraising success	
	(1)	(2)
Individual analyst rating	0.053***	0.051***
	[8.05]	[8.62]
Individual analyst rating × ICO with highest visibility	0.029***	0.036***
	[2.96]	[4.54]
ICO with highest visibility	-0.134***	-0.161***
	[-3.12]	[-5.06]
No. of analysts	0.004***	0.004***
	[3.54]	[3.08]
Fraction of tokens for sale	-0.081	-0.078
	[-1.23]	[-1.13]
Presale	0.098***	0.091**
	[4.78]	[4.25]
High bonus	-0.024	-0.032
	[-0.70]	[-0.95]
Know Your Customer	0.035*	0.036*
	[2.18]	[2.20]
Multiple languages	0.053**	0.044*
	[2.98]	[2.10]
Multiple currencies	0.038	0.042
	[1.66]	[1.83]
STO	0.169***	0.161***
	[3.32]	[2.79]
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	0.27	0.28
% (Dep variable = 1)	67.5%	67.5%

Table 9: Token Performance

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 91th, 182th, and 365th trading days, respectively. Three-month, six-month, and one-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 three months, six months, and one year after being listed on CoinMarketCap, respectively. *Delisting in three months* is a dummy variable that equals 1 if a token is delisted from CoinMarketCap within three months after being listed and 0 otherwise. *Delisting in six months* and *Delisting in one year* are similarly defined.

	Average	25th Percentile	Median	75th Percentile	Std. Dev.	Obs.
	(1)	(2)	(3)	(4)	(5)	(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 three months	0.008	0	0	0	0.088	771
Delisting in six months	0.026	0	0	0	0.160	718
Delisting in one year	0.081	0	0	0	0.273	468

Table 10: Analyst Ratings and Long-Run Token Performance

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, six-month, and one-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 and are measured immediately before ICO start dates. 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. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Three-month return		Six-month return		One-year return	
	OLS	Median regression	OLS	Median regression	OLS	Median regression
	(1)	(2)	(3)	(4)	(5)	(6)
Analyst rating	0.213*	0.066	0.331**	0.102**	0.416***	0.087**
	[1.80]	[1.32]	[1.98]	[2.09]	[2.97]	[2.56]
No. of analysts	-0.009	-0.001	-0.017*	-0.002**	-0.007	0.001
	[-1.24]	[-0.31]	[-1.93]	[-2.46]	[-0.70]	[0.29]
Fraction of tokens for sale	0.543*	-0.117	0.861	0.039	0.095	0.040
	[1.78]	[-0.95]	[1.17]	[0.41]	[0.28]	[0.23]
Presale	-0.197	-0.086**	-0.136	0.000	-0.657***	-0.006
	[-1.35]	[-2.47]	[-1.32]	[0.02]	[-3.41]	[-0.55]
High bonus	-0.271***	-0.041	-0.065	0.002	-0.805***	-0.018
	[-2.61]	[-0.63]	[-0.34]	[0.08]	[-3.78]	[-0.36]
Know Your Customer	0.066	0.059	-0.015	0.041	-0.197	-0.008
	[0.34]	[0.74]	[-0.07]	[1.29]	[-0.40]	[-0.12]
Multiple languages	-0.485**	-0.012	-0.295	0.020	-0.302***	-0.012
	[-2.56]	[-0.21]	[-1.63]	[0.53]	[-2.72]	[-1.43]
Multiple currencies	-0.107	-0.009	-0.076	0.019**	-0.003	0.036***
	[-0.80]	[-0.25]	[-0.42]	[2.03]	[-0.02]	[31.51]
STO	-0.421	0.237	-0.344	-0.035	0.140	0.066
	[-0.64]	[0.25]	[-0.67]	[-0.09]	[0.23]	[0.17]
First-day excess return	-0.099***	-0.027***	-0.093**	-0.020***	-0.079**	-0.003
	[-5.29]	[-3.19]	[-2.23]	[-7.13]	[-1.98]	[-0.84]
Three-month market return	1.046***	0.692***				
	[6.87]	[4.57]				
Six-month market return			1.694***	0.844***		
			[4.46]	[6.03]		
One-year market return					0.305**	0.413***
					[3.20]	[4.41]
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	0.15		0.38		0.36	
Pseudo R-squared		0.12		0.19		0.29

Table 11: Analyst Ratings, Token Volatility and Delisting

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 three months, six months, and one year after being listed on CoinMarketCap, respectively. *Delisting in three months* is a dummy variable that equals 1 if a token is delisted from CoinMarketCap within three months after being listed and 0 otherwise. *Delisting in six months* and *Delisting in one year* are similarly defined. All independent variables are as defined in Table 2 and are measured immediately before ICO start dates. In each column we report coefficient estimates and their t-statistics. Standard errors are clustered at the quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Three-month volatility (1)	Six-month volatility (2)	One-year volatility (3)	Delisting in three months (4)	Delisting in six months (5)	Delisting in one year (6)
Analyst rating	-0.426**	-0.314*	-0.190**	-0.014**	-0.035***	-0.089**
	[-2.99]	[-1.90]	[-2.36]	[-2.55]	[-4.25]	[-2.48]
No. of analysts	-0.008	-0.014**	-0.015*	0.000	-0.000	0.000
	[-1.35]	[-2.23]	[-1.96]	[0.23]	[-0.93]	[0.27]
Fraction of tokens for sale	0.141	0.113	0.089	-0.027	-0.018	0.001
	[0.47]	[0.54]	[0.21]	[-1.76]	[-0.53]	[0.02]
Presale	0.043	0.054	-0.097	-0.009	0.002	0.002
	[0.33]	[0.41]	[-0.70]	[-1.08]	[0.19]	[0.08]
High bonus	0.228	0.226	0.261	-0.002	-0.011	-0.013
	[0.95]	[1.19]	[0.92]	[-0.15]	[-0.38]	[-0.44]
Know Your Customer	0.277	0.0757	-0.183	0.011	-0.004	-0.009
	[1.66]	[0.90]	[-1.21]	[1.46]	[-0.39]	[-0.62]
Multiple languages	-0.340*	-0.225	-0.059	-0.010	-0.028*	-0.042**
	[-1.87]	[-1.24]	[-0.37]	[-1.36]	[-1.97]	[-2.57]
Multiple currencies	0.169	0.146	0.054	0.016**	0.020*	-0.000
	[1.60]	[0.95]	[0.35]	[2.24]	[1.81]	[-0.01]
STO	-0.139	-0.122	0.288	-0.007	-0.059***	-0.109**
	[-0.39]	[-0.37]	[0.76]	[-0.42]	[-4.09]	[-2.27]
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	0.20	0.22	0.23	0.00	0.01	0.13
% (Dep variable =1)	N/A	N/A	N/A	0.01	0.03	0.08

INTERNET APPENDIX

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

Appendix I

1 A changing regulatory environment

During the past few years, ICOs and cryptocurrency exchanges have operated in a legal and regulatory grey 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 has recently charged a number of fraudulent ICOs, such as AriseBank and Centra Tech. In May 2018, more than 40 state and provincial jurisdictions in the U.S. 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, (2) market participants must ensure that their cryptocurrency activities do not undermine their anti-money laundering and KYC obligations. In April 2019, the SEC published a non-legally binding framework for analyzing whether a token sold through an ICO qualifies as a security.[1]

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. 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

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

while some tokens qualify as securities under the existing regulations, others do not.

Due to 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 U.S., China and certain other countries from participating in their offerings.

2 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 anti-money laundering and KYC policies can be automated within an STO system, as well as dividend management and distribution procedures.

With the downfall of ICOs in 2019, the crypto fundraising industry has witnessed another form of token sales – 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 can also 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.

3 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.

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 whitepaper in both English and Chinese on April 20, 2017, introducing its business model, functioning of the organization and features of the token.[2] Aragon is among the few ICOs that require a relatively long vesting period for founders, who will vest 25% of their tokens every six months after the sale (two-year vesting with six-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'.[3]

On the same day, the token sale was officially announced in a blog post on Aragon's website. The sale was originally planned for four weeks, from May 17 to June 14, 2017. Aragon sought to sell 70% of tokens to investors, and accepted only ETH. In the first two 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.

Due to 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 A3, Panel A plots minute-by-minute investor contributions and the cumulative

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

[3] 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.

contributions, which indicates that within seven 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.

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.

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 two 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, 2020).

4 Discussions on incentives and endogeneity issues

One of the concerns on the analysis on platform-driven incentives is that whether the analyst with the highest visibility in an ICO knows whether he/she will get eventually the highest visibility in the ICO. The relative visibility is eventually decided after all ratings are issued for the ICO. In order to understand the nature of the relative timing of issuance of the rating, we regress *Days elapsed since the first rating* on *ICO with highest visibility*. *Days elapsed since the first rating* is the number of days elapsed since the first rating for an ICO was issued. Therefore, by construction, *Days elapsed since the first rating* for the analyst who issued the rating first in an ICO is 0.

[Insert Table A9 here.]

In Table A9, Panel A, we report the results of the regressions that regress *Days elapsed since the first rating* on *ICO with highest visibility*. In column (1), we observe that the analyst with *ICO with highest visibility* on average issue ratings 14.78 days later than other analysts. The number of sample size is only slightly smaller than that of column (1) of Table 8 because we only choose the ICOs that received more than one rating by individual analysts. Note that we use ICO fixed effects to compare *Days elapsed since the first ratings* of analysts in each ICO and analyst fixed effects as well to control for any analyst specific effects. In column (2), we regress log(1+ *Days elapsed since the first ratings*) on *ICO with highest visibility* dummy under the same regression specification to see if the the result in column (1) is entirely driven by a few of outliers. We find the qualitatively similar result. Overall, the results suggest that analysts with higher visibility tend to issue a bit later than the others on average. Therefore, they are more likely to know their relative visibility than other analysts in a given ICO.

In Panel B, we investigate whether the analyst with the highest visibility provides any additional information when he/she issues the rating using ICO-level regressions. Da and Huang (2020) study wisdom of crowds in an online platform, Estimize, where analysts issue earning forecasts on publicly listed firms. They provide evidence that individual analysts' earning forecasts are affected by publicly available information including other analysts' forecasts. One of the biggest difference between Estimize and ICObench is that a vast majority of the analysts in Estimize platform are finance professionals who are working in finance industry whereas a vast majority of analysts in ICObench are nonprofessionals. Therefore, it is not clear whether analysts in ICObench would behave differently. For example, given that a vast majority of analysts in ICObench are nonprofessionals, a herding behavior by analysts who issue ratings later than the others could be very strong. Therefore, in an extreme case, it is possible that the late analysts do not use their private information at all and only aggregate the previously issued ratings to produce a relatively more precise rating.

Given that the analysts with highest visibility issue ratings relatively later than the others on average, one could argue that they simply aggregate the previous ratings to produce more accurate rating. In this case, while the their ratings could be more accurate, their ratings do not add any additional information on top of the previous ratings. To mitigate this concern, we investigate whether the ratings by analysts with highest visibility have any incremental power in explaining the fundraising success. In this analysis, we only use a subset of ICOs where more than one individual analyst issue ratings and the analysts with highest visibility are not the first analysts who issue the ratings. Therefore, the sample size is smaller than that of our baseline results in Table 3.

In column (1) of Panel B, we regress the rating of the highest visible analyst on *Previous rating 1*. *Previous rating 1* is average of the ratings issued before the rating issued by the analyst with the highest visibility in the ICO. The result shows that the rating of the highest visible analyst is highly correlated with *Previous rating 1*. In column (3), we regress *Fundraising success* on the residual obtained from the regression of column (1) and other control variables including *Previous rating 1*. The residual is a proxy for incremental information produced by analysts with highest visibility. The coefficient for the *Residual from column (1)* is positive and statistically significant, which implies that the rating issued by the analyst with the highest visibility provides additional information to explain the fundraising success on top of the previously issued ratings. In column (2) and (4), we perform a similar analysis using a different definition of *Previous rating*. *Previous rating 2* is the average rating of analysts whose weights are maximum among the ratings issued before the rating by the analyst with highest visibility. We observe qualitatively similar results.

While our results suggest that the specific feature of the platform, showing the analyst with highest weight at the top of the ratings page of an ICO, helps induce analysts to issue informative ratings, the platform might not have been optimally designed to fully harness wisdom of crowds. Da and Huang (2020) find that analysts tend to heavily rely on public information when it is available. While using public information on top of their private information increases the forecasting accuracy, the aggregate forecast that combines the forecasts of individual analysts becomes more accurate when the analysts only use private information. In the ICObench platform, however, analyst ratings are publicly available and therefore, analysts can see others' ratings, which could discourage them to fully reveal their private information.

Appendix II

Figure A1: An Illustration of the ICO Timeline
This timeline illustrates the timing of events for a typical ICO. A pre-announcement 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 whitepaper 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.

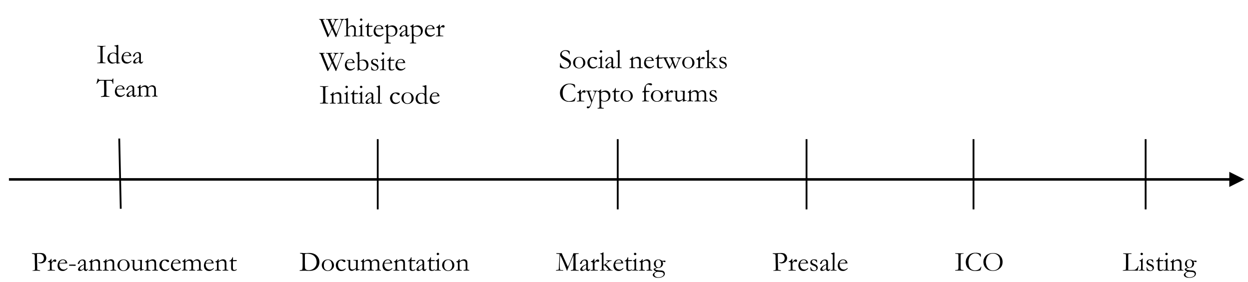
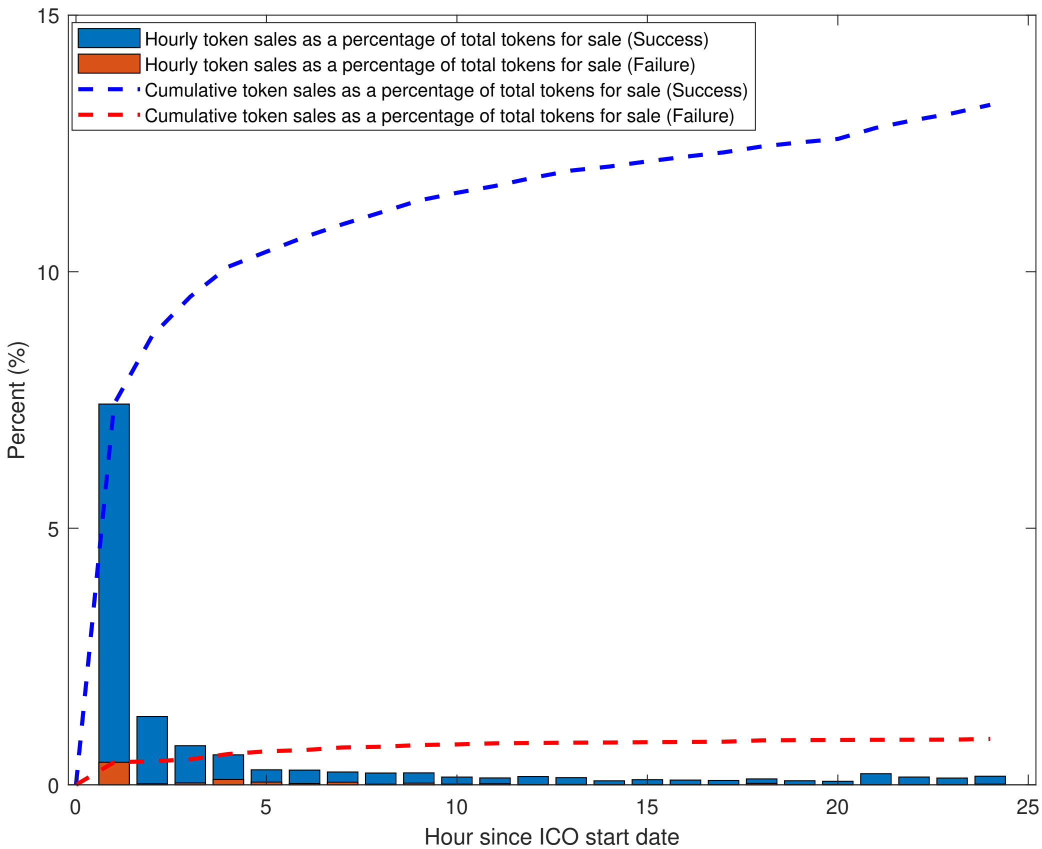


Figure A2: Primary Market Subscriptions in ICOs

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. In Panel A, the the blue (red) bars plot the average hourly token sales on the first day of ICO for successful and failed ICOs. The blue (red) dotted line plots the cumulative hourly token sales as a percentage of total tokens for sale in successful (failed) ICOs. Panel B repeats the analysis for each block during the first hour of token sales. A block contains transactions within an approximately 14-second interval. 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.

Panel A. Hourly token sales on the first day of an ICO



Panel B. Block-by-block sales during the first hour of an ICO

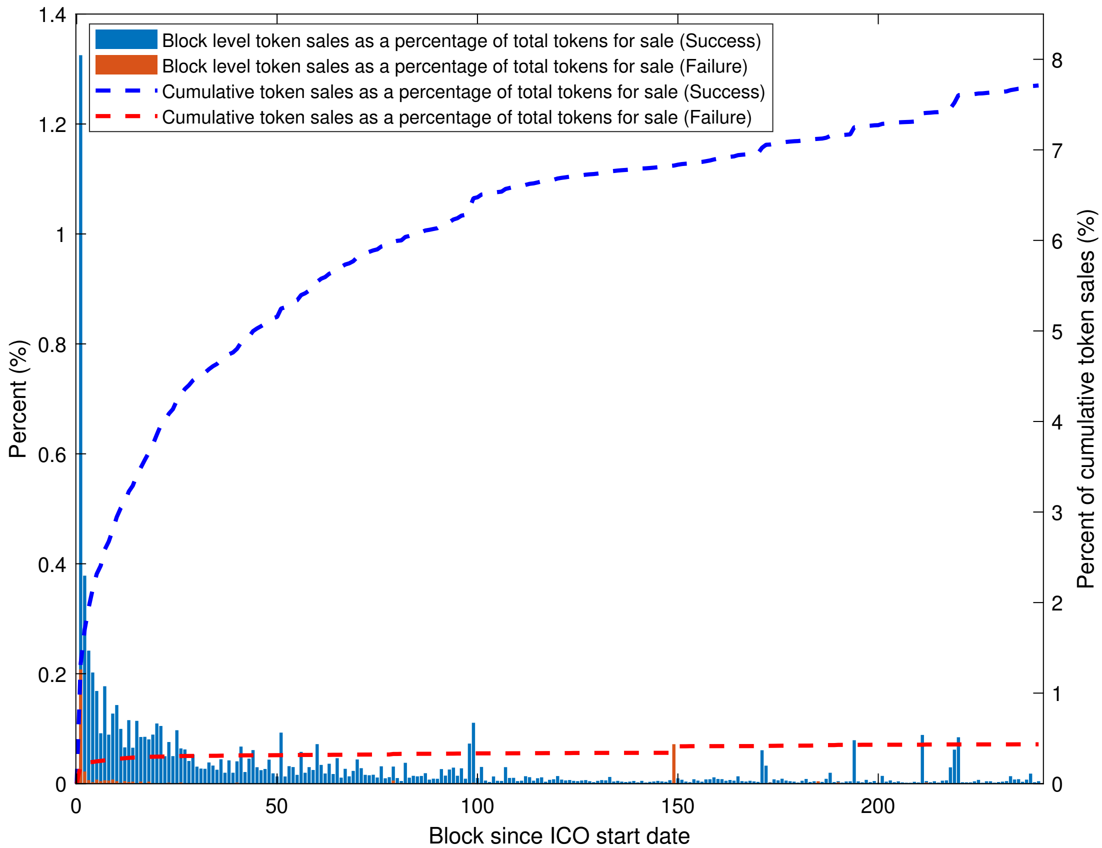
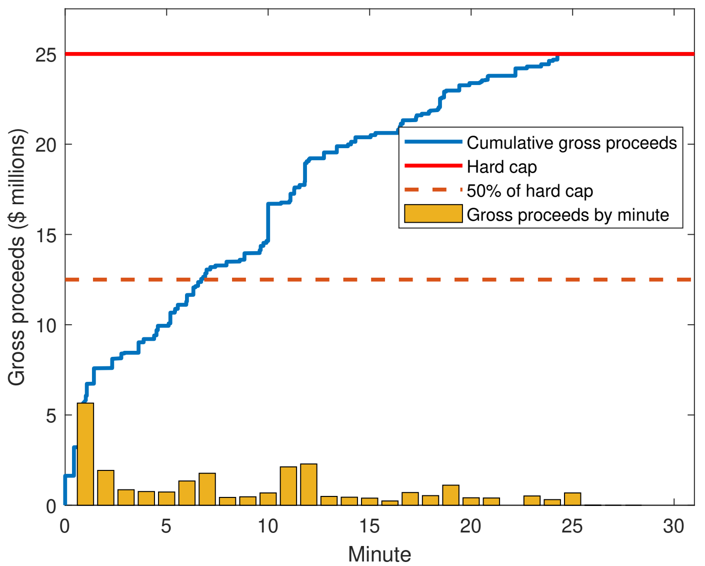


Figure A3: The Aragon Token Sale

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 percent of largest holders.

Panel A. Token subscription in Aragon Network



Panel B. Aragon token distribution by investor

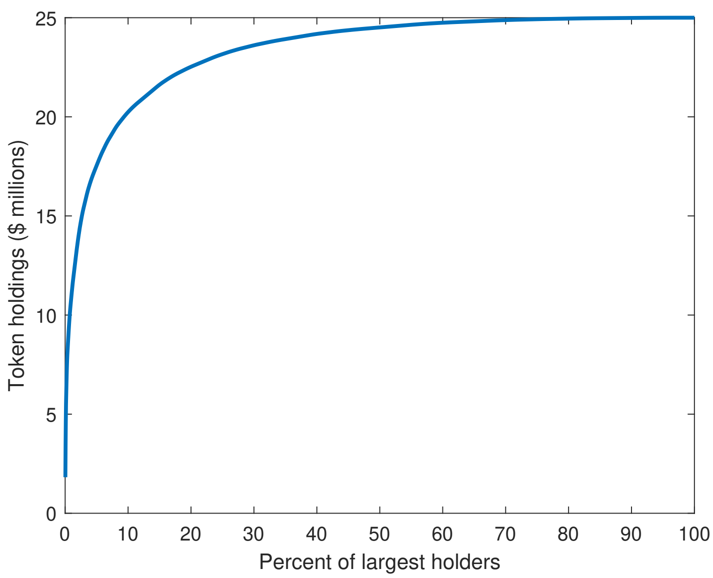


Table A1: Differences between ICOs and IPOs

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

	ICO	IPO
1. Pre-announcement	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	- Whitepaper - 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

Table A2: Top 10 ICOs by Gross Proceeds

This table lists the top 10 ICOs by gross proceeds as of December 31, 2018. The ticker for each token is shown in the parenthesis next to the startup name. Information for each ICO is collected from ICObench, and the whitepaper and website for the token sale.

	Startup Name	ICO Start - End	Gross Proceeds ($)
	EOS (EOS)	6/26/2017 - 6/1/2018	4,198,000,000
	TaTaTu (TTU)	6/11/2018 - 6/30/2018	575,000,000
	Dragon Coin (DRG)	2/15/2018 - 3/15/2018	320,000,000
	Huobi (HT)	1/24/2018 - 2/28/2018	300,000,000
	HADC (DAC)	11/27/2017 - 12/22/2017	258,000,000
	Filecoin (FIL)	8/10/2017 - 9/10/2017	257,000,000
	Tezos (XTZ)	7/1/2017 - 7/13/2017	232,000,000
	Sirin Labs (SRN)	12/12/2017 - 12/26/2017	157,886,000
	The Bancor Protocol (BNT)	6/12/2017 - 6/12/2017	153,000,000
	Bankera (BNK)	11/27/2017 - 2/27/2018	151,800,000

Table A3: ICOs by Country and Industry

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.

Panel A. Most popular countries of incorporation

Country	No. of ICOs	Percent of total	Fundraising success rate	Percent listed on exchanges
United States	451	13.3%	42.1%	30.2%
Singapore	334	9.8%	51.8%	32.9%
United Kingdom	301	8.9%	38.5%	18.7%
Russia	242	7.1%	33.9%	20.7%
Switzerland	174	5.1%	54.0%	29.9%
Estonia	169	5.0%	45.6%	13.0%
China (including Hong Kong)	150	4.4%	48.0%	33.3%
Germany	77	2.3%	39.0%	18.2%
Canada	72	2.1%	44.4%	22.2%
Australia	72	2.1%	38.9%	20.8%
Sum of the above	2,042	60.2%	43.8%	25.5%
Total (all countries)	3,392	100%	42.4%	23.9%

Panel B. Most popular industries

Industry	No. of ICOs	Percent of total	Fundraising success rate	Percent listed on exchanges
Financial Services	407	12.0%	46.2%	27.8%
Exchanges and Wallets	222	6.5%	41.4%	21.6%
Investment	185	5.5%	43.2%	20.0%
Blockchain Infrastructure	178	5.2%	59.0%	44.4%
Gaming and Virtual Reality	161	4.7%	47.2%	26.7%
Trading	157	4.6%	52.2%	29.3%
Social Media and Communication	145	4.3%	40.0%	21.4%
Commerce and Retail	143	4.2%	35.0%	17.6%
Business Services and Consulting	140	4.1%	43.6%	25.0%
Marketing and Advertising	137	4.0%	45.3%	24.1%
Sum of the above	1,875	55.2%	45.4%	25.7%
Total (all industries)	3,392	100%	42.4%	23.9%

Table A4: Determinants of ICO Success – Probit Model

This table replicates Table 3 except that it reports results from a probit model. All independent variables are as defined in Table 2. In each column, we report coefficient estimates, their t-statistics, and the marginal probability change induced by a one-unit change in the value of a specific covariate from its sample average. Standard errors are clustered at the quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Fundraising success			Exchange listing		
	Coefficient	t-stat.	Marg. Prob.	Coefficient	t-stat.	Marg. Prob.
ICO characteristics	(1)	(2)	(3)	(4)	(5)	(6)
Analyst rating	0.522***	9.20	20.7%	0.682***	8.96	16.0%
No. of analysts	0.025***	5.39	1.0%	0.015***	3.32	0.4%
Fraction of tokens for sale	-0.805***	-7.78	-31.9%	-0.855***	-5.25	-20.1%
Presale	0.128**	2.21	5.1%	0.057	0.63	1.3%
High bonus	-0.111***	-2.90	-4.4%	-0.231***	-5.01	-5.1
Know Your Customer	-0.043	-0.96	-1.7%	-0.037	-0.50	-0.9%
Multiple languages	0.201***	4.50	8.0%	0.353***	3.59	8.6%
Multiple currencies	0.102*	1.79	4.0%	0.089**	2.20	2.1%
STO	0.434**	2.05	17.1%	0.444*	1.73	8.1%
Quarterly dummies	Yes			Yes		
Industry dummies	Yes			Yes		
Country dummies	Yes			Yes		
Observations	3,392			3,392		
Pseudo R-squared	0.21			0.35		
% (Dep variable = 1)	42.4%			23.9%		

Table A5: ICO Duration

This table relates token sale completion to ICO characteristics. The sample consists of a total of 3,392 ICOs from January 1, 2016 to December 31, 2018 that were completed as of March 31, 2019. In columns (1) and (2), the dependent variable is the logarithm of the number of days between ICO kickoff and completion. All independent variables are as defined in Table 2, and are measured immediately before the ICO start date. Columns (1) and (2) report results of an OLS model, while in columns (3)-(5), we apply a Cox proportional hazards model (Cox, 1972) to estimate the hazard rate on a daily frequency for ICO completion. In all specifications, we report coefficient estimates and their robust t-statistics. Standard errors are clustered at the quarter level for the OLS regressions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable: # Days to completion	OLS		Cox model		
	Coefficient	t-stat.	Coefficient	z-stat.	Hazard ratio
	(1)	(2)	(3)	(4)	(5)
Analyst rating	-0.138***	-3.06	0.061**	2.21	1.062
No. of analysts	-0.001	-0.21	0.001	0.22	1.001
Fraction of tokens for sale	0.183***	3.05	-0.151*	-1.67	0.860
Presale	-0.052	-0.67	0.111***	2.63	1.117
High bonus	0.303***	8.57	-0.231***	-6.19	0.794
Know Your Customer	0.105**	2.37	-0.112**	-2.55	0.894
Multiple languages	-0.009	-0.31	0.001	0.02	1.001
Multiple currencies	0.198***	7.16	-0.200***	-5.50	0.819
STO	0.167**	2.37	-0.176*	-1.68	0.839
Quarterly dummies	Yes		Yes		
Industry dummies	Yes		Yes		
Country dummies	Yes		Yes		
Observations	3,392		188,226		
Adj. R-squared	0.17				
Wald Chi-squared			6,243.21		

Table A6: Determinants of Analyst Ratings

This table reports results on the determinants of analyst ratings for all ICOs that started between January 1, 2016 and December 31, 2018, and were completed as of March 31, 2019. *Analyst rating* is the average rating (scale 1-5) for an ICO by analysts on ICObench. *Market return during last quarter (month)* is last quarter's (month's) compounded daily return on the value-weighted index of Ethereum and Bitcoin. *Log (Bitcoin price at last quarter end)* is the logarithm of the Bitcoin price at last quarter end before ratings are issued. *Log (Ethereum price at last quarter end)*, *Log (Bitcoin price at last month end)*, *Log (Ethereum price at last month end)* are defined similarly. All other variables are as defined in Table 2, and are measured immediately before the ICO start date. In each column, we report coefficient estimates and their *t*-statistics. Standard errors are clustered at the quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	Analyst rating				
	(1)	(2)	(3)	(4)	(5)
Fraction of tokens for sale	-0.242***	-0.245***	-0.241***	-0.242***	-0.234***
	[-3.91]	[-3.99]	[-4.01]	[-3.91]	[-3.67]
Presale	0.213***	0.217***	0.214***	0.209***	0.212***
	[8.15]	[8.18]	[7.61]	[9.96]	[7.72]
High bonus	0.045*	0.046**	0.045*	0.045**	0.048*
	[1.79]	[2.03]	[1.92]	[2.12]	[1.91]
Know Your Customer	0.364***	0.369***	0.364***	0.363***	0.378***
	[9.34]	[11.48]	[10.58]	[10.99]	[11.03]
Multiple languages	0.302***	0.302***	0.302***	0.301***	0.297***
	[6.99]	[7.02]	[7.13]	[7.15]	[6.75]
Multiple currencies	0.100***	0.100***	0.100***	0.097***	0.100***
	[4.60]	[4.67]	[4.78]	[4.37]	[4.63]
STO	0.095	0.094	0.094	0.088	0.072
	[0.93]	[0.90]	[0.97]	[0.83]	[0.66]
Market return during last quarter	-0.009				
	[-0.66]				
Log (Bitcoin price at last quarter end)		0.008			
		[0.17]			
Log (Ethereum price at last quarter end)		-0.020			
		[-0.42]			
Market return during last month			-0.023		
			[-0.26]		
Log (Bitcoin price at last month end)				0.082	
				[1.56]	
Log (Ethereum price at last month end)				-0.060	
				[-1.38]	
Quarterly fixed effects	No	No	No	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,392	3,392	3,392	3,392	3,392
Adj. R-squared	0.22	0.22	0.22	0.22	0.22

Table A7: Analyst Turned Advisors and ICO Success

In this table, we examine whether analyst turned advisors improve the odds of ICO success. *Fundraising success* is an indicator equal to 1 if an ICO reachesits soft cap or the project raises more than $0.5 million in the absence of a soft cap. *Analyst rating* is the average rating (scale 1-5) for an ICO by analysts on ICObench. *Top 10 analyst advisor* is a dummy variable equal to 1 if at least one advisor on the ICO team was an "Top 10" analyst, an ICObench designation based on analysts' track records, and 0 otherwise. All other independent variables are as defined in Table 2, and are measured immediately before the ICO start date. In each column we report coefficient estimates and their t-statistics. Standard errors are clustered at the quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Fundraising success		Analyst rating
	(1)	(2)	(3)
Top 10 analyst advisor	0.192***	0.058*	0.569***
	[4.06]	[1.89]	[5.81]
Analyst rating		0.165***	
		[7.90]	
Fraction of tokens for sale	-0.289***	-0.253***	-0.242***
	[-10.18]	[-9.91]	[-3.82]
Presale	0.082***	0.041**	0.208***
	[3.80]	[2.23]	[7.46]
High bonus	-0.030**	-0.040***	0.048*
	[-2.64]	[-3.56]	[2.09]
Know Your Customer	0.069***	-0.007	0.364***
	[4.24]	[-0.45]	[11.56]
Multiple languages	0.134***	0.070***	0.294***
	[9.19]	[5.09]	[6.60]
Multiple currencies	0.051**	0.028	0.099***
	[2.83]	[1.57]	[4.72]
STO	0.170**	0.157**	0.092
	[2.06]	[2.22]	[0.91]
Quarterly fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Observations	3,392	3,392	3,392
Adj. R-squared	0.15	0.23	0.22
% (Dep variable = 1)	42.4%	42.4%	N/A

Table A8: Potentially Fraudulent ICOs

Our sample includes 3,392 ICOs on ICObench that started between January 1, 2016 and December 31, 2018, and were completed as of March 31, 2019. Panel A reports characteristics of the 262 ICOs with missing whitepapers (treatment ICOs), and compare them to ICOs with downloadable whitepapers (controls). Panel B shows characteristics of the 41 ICOs charged by U.S. regulators (treatment ICOs), and compare them to the rest of our sample (controls). All variables are as defined in Table 3. In both panels, columns (1)-(3) report the average, median and standard deviation of characteristics for treatment ICOs. Columns (4) and (5) show the differences in average characteristics between treatment and control ICOs and their associated t-statistics. Column (6) reports the Wilcoxon signed rank statistics, which are asymptotically normal, for the median differences.

Panel A. ICOs with missing whitepapers

	ICOs with missing whitepapers			Difference between ICOs with and without missing whitepapers		
	Average (1)	Median (2)	Std. Dev. (3)	Diff. in Avg. (4)	t-stat. (5)	Wilcoxon (6)
Ex post characteristics						
Fundraising success	0.271	0	0.445	-0.165	-5.22	-5.22
Exchange listing	0.130	0	0.337	-0.118	-4.33	-4.33
Gross proceeds ($ million)	6.820	2.068	10.503	-4.979	-1.75	-3.28
Gross proceeds/Hard cap	0.413	0.204	0.480	-0.027	-0.47	-1.06
No. of subscribers	310.122	0	1,218.129	-691.080	-2.25	-4.45
Duration of offering (days)	50.257	32.000	40.436	-4.405	-1.44	-0.70
Ex ante characteristics						
Analyst rating	2.562	2.600	0.751	-0.613	-12.41	-11.68
No. of analysts	2.290	1.000	2.708	-2.586	-5.31	-6.19
Soft cap ($ million)	8.855	1.500	60.419	3.887	2.41	-2.49
Hard cap ($ million)	35.704	16.602	83.046	-11.628	-0.47	-2.31
Fraction of tokens for sale	0.647	0.700	0.193	0.076	5.81	5.83
Presale	0.500	0	0.501	-0.113	-3.59	-3.59
High bonus	0.332	0	0.472	-0.012	-0.40	-0.40
Know Your Customer	0.252	0	0.435	-0.151	-4.83	-4.83
Whitelist	0.160	0	0.368	-0.116	-4.09	-4.09
Participation restriction	0.260	0	0.439	-0.133	-4.28	-4.28
Multiple languages	0.118	0	0.324	-0.235	-7.81	-7.81
Multiple currencies	0.382	0	0.487	-0.066	-2.06	-2.06
STO	0.019	0	0.137	-0.002	-0.22	-0.22

Panel B. ICOs charged by U.S. regulators

	ICOs with regulatory actions			Difference between ICOs with and without regulatory actions		
	Average (1)	Median (2)	Std. Dev. (3)	Diff. in Avg. (4)	t-stat. (5)	Wilcoxon (6)
Ex post characteristics						
Fundraising success	0.268	0	0.449	-0.157	-2.04	-2.04
Exchange listing	0.098	0	0.300	-0.143	-2.14	-2.14
Gross proceeds ($ million)	5.857	0.998	9.390	-5.730	-0.96	-2.31
Gross proceeds/Hard cap	0.231	0.049	0.350	-0.209	-1.74	-2.90
No. of subscribers	34.813	3	86.706	-906.764	-1.08	-1.33
Duration of offering (days)	56.795	41.000	51.978	2.502	0.33	-0.03
Ex ante characteristics						
Analyst rating	2.793	2.700	0.784	-0.340	-2.75	-2.83
No. of analysts	3.561	1.000	4.544	-1.129	-0.94	-0.97
Soft cap ($ million)	34.052	2.500	152.520	29.122	7.33	0.19
Hard cap ($ million)	62.397	25.325	172.241	16.113	0.27	0.98
Fraction of tokens for sale	0.604	0.600	0.159	0.028	0.85	0.68
Presale	0.585	1	0.499	-0.019	-0.25	-0.25
High bonus	0.293	0	0.461	-0.051	-0.69	-0.69
Know Your Customer	0.195	0	0.401	-0.199	-2.59	-2.59
Whitelist	0.098	0	0.300	-0.172	-2.47	-2.47
Participation restriction	0.220	0	0.419	-0.165	-2.16	-2.16
Multiple languages	0.293	0	0.461	-0.043	-0.58	-0.58
Multiple currencies	0.512	0	0.506	0.071	0.90	0.90
STO	0.049	0	0.218	0.028	1.25	1.25

Table A9: Do Analysts with Highest Visibility Provide Additional Information? In this table, we report whether the analyst with highest visibility in an ICO issues the rating relatively late and he/she provides any additional information that explains the fundraising success on top of the previously issued ratings. In Panel A, *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 0. In Panel B, we perform an ICO-level analysis using the subset of ICOs where the analyst with the highest visibility did not issue the rating first. *Rating of the highest visible analyst* is the rating by the analyst with the highest visibility in an ICO. *Previous rating 1* is the average of the ratings issued before the rating issued by the analyst with the highest visibility in the ICO. To compute *Previous rating 2*, we choose the ratings before the analyst with the highest visibility issued his/her rating. *Previous rating 2* is the average rating of analysts whose weights are the highest among them. In each column we report coefficient estimates and their t-statistics. In Panel A(B), standard errors are clustered at the analyst×quarter level (quarter level). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Highest visibility and timing of rating

Dependent variable:	Days elapsed since the first rating	log(1+Days elapsed since the first rating)
	(1)	(2)
ICO with highest visibility	14.78***	0.206**
	[3.94]	[2.02]
ICO fixed effects	Yes	Yes
Analyst fixed effects	Yes	Yes
Observations	12,259	12,259
Adj. R-squared	0.62	0.42

Panel B. Informativeness of ratings issued by analysts with highest visibility

Dependent variable:	Rating of the highest visible analyst		Fundraising success	
	(1)	(2)	(3)	(4)
Previous rating 1	0.581***		0.113***	
	[14.86]		[10.02]	
Previous rating 2		0.502***		0.081***
		[15.27]		[10.57]
Residual from column (1)			0.041**	
			[2.71]	
Residual from column (2)				0.051***
				[3.75]
No. of analysts	0.003	0.004	0.007***	0.007***
	[1.06]	[1.31]	[5.33]	[5.38]
Fraction of tokens for sale	-0.127	-0.101	-0.149***	-0.148***
	[-0.47]	[-0.38]	[-3.31]	[-3.66]
Presale	0.178**	0.217***	0.129***	0.134***
	[2.86]	[3.50]	[5.41]	[5.58]
High bonus	-0.069	-0.067	-0.028	-0.027
	[-1.19]	[-1.11]	[-0.73]	(-0.69)
Know Your Customer	0.060	0.073	0.022	0.030
	[0.98]	[1.19]	[0.51]	[0.73]
Multiple languages	0.115*	0.108	0.048***	0.049***
	[2.04]	[1.73]	[3.38]	[3.28]
Multiple currencies	0.013	0.032	0.020	0.025
	[0.18]	[0.44]	[0.81]	[1.03]
STO	0.182	0.263	0.166***	0.178***
	[0.92]	[1.32]	[4.20]	[4.22]
Quarterly fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	1,103	1,103	1,103	1,103
Adj. R-squared	0.34	0.33	0.19	0.18
% (Dep variable = 1)	N.A.	N.A.	61.1%	61.1%

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