

Barth, Andreas; Laturnus, Valerie; Mansouri, Sasan; Wagner, Alexander

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ICO analysts

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ICO Analysts*

Andreas Barth, Valerie Laturus, Sasan Mansouri and Alexander F. Wagner[†]

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ABSTRACT

Freelancing human experts play an important role in Initial Coin Offerings (ICOs). Expert ratings partially reflect the reciprocal network of ICO members and analysts. Ratings predict ICO success, but highly imperfectly so. Favorably rated ICOs tend to fail when more ratings reciprocate prior ratings. Failure despite strong ratings is also frequent when analysts have a history of optimism, and when reviews strike a particularly positive tone. These findings help illuminate the workings of ICOs for funding new ventures, and the rich data and the specific institutional setup also yield insights pertinent to the literature on equity analysts and rating agencies.

JEL classification: G14, G24, L26, D82, D83

Keywords: Analysts, Asymmetric Information, FinTech, Initial Coin Offering (ICO)

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[†]Barth, Laturus and Mansouri are with Goethe University Frankfurt, Wagner is with University of Zurich, CEPR, ECGI and SFI. ✉: Andreas.Barth@finance.uni-frankfurt.de ; Laturus@finance.uni-frankfurt.de ; mansouri@finance.uni-frankfurt.de ; alexander.wagner@bf.uzh.ch

1 Introduction

Initial Coin Offerings (ICOs) are token sale events on an own or existing blockchain that facilitate the financing of an entrepreneurial venture. This paper investigates determinants and consequences of the quantitative and qualitative aspects of ICO ratings issued by human experts (henceforth ICO analysts). Ratings predict the success of ICOs, but highly imperfectly. Even among ICOs with an average rating in the top quartile more than 50% fail. As a novel contribution, the analysis addresses potential conflicts of interest in ICO analyst ratings. We find that ICO analysts tend to reciprocate favorable ratings for their own ventures; however, the results also suggest that investors place lower emphasis on reciprocating ratings.

Studying ICOs and their analysts is of interest for three reasons. First, the offering of tokens is a potentially powerful instrument for new ventures to obtain crowdfunding-like resources (Goldstein et al., 2019; Lyandres, 2019; Chod and Lyandres, 2020; Lee and Parlour, 2020; Li and Mann, 2020; Lyandres et al., 2020; Gryglewicz et al., 2020), not least because of the underlying distributed ledger-based technology and the platform’s special features (Biais et al., 2019; Cong and He, 2019; Easley et al., 2019; Hinzen et al., 2020). Therefore, understanding the workings of this relatively new market for the funding of companies and products is important, particularly given that regulation is only beginning to clarify.¹

Second, like financial analysts or rating agencies, ICO analysts suffer from potential conflicts of interests.² In fact, these conflicts are potentially more extreme here. ICO analysts do not only *provide ratings* for ICOs, but they may also *run their own* ICOs. Thus, whenever an ICO analyst i provides a rating for an ICO j , there is a chance that any team member of this ICO j will provide a rating for the ICO of analyst i at a later stage. The literature

¹The U.S. Securities and Exchange Commission (SEC) does consider tokens to be securities, and it has recently won a landmark lawsuit against Telegram for violation of federal securities laws in the course of its ICO. See <https://www.sec.gov/news/press-release/2020-146>. European economies tend to be significantly less stringent in their regulatory approaches, see Kaal (2018); thinkBLOCKtank (2019).

²See Lin and McNichols (1998), Chan et al. (2007) or Michaely and Womack (2015) for evidence of biased financial analysts and Bolton et al. (2012) or Bar-Isaac and Shapiro (2013) for biased rating agencies.

on financial analysts suggests that a close link between analysts and firms leads to superior information and better assessments (Bradley et al., 2017; Bae et al., 2008), but also highlights the problem of conflicts of interest in a similar spirit of “affiliated” analysts (Malmendier and Shanthikumar, 2007) or revolving door analysts (Lourie, 2019; Kempf, 2020). A similar conflict of interest is present for rating agencies to distort ratings in favor of issuers (Chu and Rysman, 2019), in particular when issuers additionally hire rating agencies for non-rating services (Baghai and Becker, 2017). Contrary to the potential bias of revolving door equity analysts that can be identified only ex post or the payments rating agencies receive from issuers that is largely hidden information, the ICO setting presents a similar situation where investors can be aware of potential biases right away.³

Third, non-professional analysts have been shown to be important information intermediaries for equity investors (Chen et al., 2014; Drake et al., 2017; Campbell et al., 2019; Farrell et al., 2020). We know, however, only little about potential conflicts of interests that such analysts face and whether market participants consider the differential credibility and informativeness of these analyses in their investment decisions.

We collect data on 5,384 ICOs between 2015 to February 2020. We identify 531 experts who issued a total of 13,834 ratings. Figure 1 illustrates some main results using binned scatter plots.

[Figure 1 about here]

We begin by investigating determinants of analysts’ ratings. We first find that analysts who, in the past, had issued very positive ratings for ICOs that did not succeed (that is, analysts with large forecast errors) provide on average lower ratings in the future (see Panel (a) of Figure 1). ICObench.com also provides a ranking of ICO analysts, which gives an equivalent setting to all-star financial analysts (Leone and Wu, 2002). We observe that “star analysts” are less optimistic and issue on average lower ratings. We do not only consider the

³The ICO setting also allows to identify more precisely potentially biased analysts compared to Malmendier and Shanthikumar (2007), where analysts were classified as “affiliated” if they belong to a bank that has an underwriting relationship with the firms they are reporting on.

quantitative ratings, but also the length and linguistic tone of the reviews that accompany the evaluation, that is, the qualitative nature of ICO analyst ratings. We observe that lower ratings come with a more negative tone of the review, and with a longer review. In all these analyses, we compare different ratings for the same ICO, which helps to rule out that these results are purely driven by the self-selection of analysts to certain ICOs.

Importantly, reciprocal ratings are special (see Panel (b) of Figure 1): the total rating score an analyst gives to an ICO j is higher if she received a rating in the past for her own ICO by any team member of coin j . This effect is stronger the higher the prior received rating was. These effects continue to hold when we compare analysts providing a rating to the same ICO in a given month.

Next, we analyze the explanatory power of ICO analyst ratings for the success of an ICO campaign, and in particular for the failure of an ICO campaign despite strong analyst endorsement. We first confirm the result of prior work that investors appear to value the fact that a human analyst provided a rating for the ICO.⁴ Moreover, a better average quantitative ICO analyst rating translates into a higher success probability for the respective ICO.

However, while the unconditional failure rate is about 64%, even among ICOs with an average rating in the top quartile 53.6% fail. Our main interest is in which characteristics of analysts or of the ICO itself lead to such disagreement between analysts' advice and the market outcome.

We find that an important determinant of failure despite high ratings is the share of reciprocal ratings:⁵ If ICO j receives a rating from many reciprocal analysts, that is, analysts who respond with their rating to a rating they received themselves from any team member of ICO j , the market is more likely to disregard analyst recommendations; see Panel (c) of Figure 1. There are two interpretations of this result. First, it is conceivable that, even

⁴This is in line with findings from other markets that ratings improve access to capital. See, e.g., Sufi (2009).

⁵This analysis thus contributes to the debate on whether or not investors are sophisticated enough to detect biased ratings (Ellis, 1998; Baker and Mansi, 2002; Livingston et al., 2010; Hirth, 2014; Badoer et al., 2019).

though we control for a wide variety of factors presumably capturing variation in quality of ICOs, reciprocal ratings occur with “objectively” bad ICOs, that is, they pick up some additional variation in quality. Second, investors may trust ICOs with more reciprocal ratings less (despite them being potentially worth funding). Either way, the findings imply that investors do not blindly pile capital into highly rated ICOs.

Interesting patterns also emerge for the linguistic measures of the rating. The length and linguistic tone of the reviews that accompany the evaluation by themselves explain only little of the variation in the success of ICOs. However, ICO failure despite high ratings is more likely the more positive the tone and the more complex the language of the reviews is.

Finally, the quantitative and qualitative ratings by human analysts do not systematically differ on average for ICOs that prove to be fraudulent. A higher share of reciprocal ratings is also not associated with a higher fraud probability, suggesting that reciprocity is not typically driven by criminal intentions. ICOs exhibiting fraud do show a larger dispersion of both rating scores and tone of rating reviews among analysts.

Overall, the results suggest that despite the apparent madness of the ICO market, investors seem to respond in a differentiated way to qualitative differences among ICO analyst ratings.

While on a general level our paper thus contributes to the overall literature on analysts, rating agencies, and conflicts of interest, it also more specifically advances our knowledge of why and for which ICO investors are willing to provide funding. Usually, the sale of tokens or ICOs appear at a very early planning stage of a life cycle of a product or a firm and suffer from severe information asymmetry and adverse selection problems (Malinova and Park, 2018; Chod and Lyandres, 2020; Chod et al., 2020; Gan et al., 2020). As such, tokens have no intrinsic value at the time of the investment but rather derive value from trust in future usage (Conley, 2017). In light of this, the literature has investigated both the supply side, i.e., choices by ICO entrepreneurs (Adhami et al., 2018; Amsden and Schweizer, 2018; Benedetti and Kostovetsky, 2018; Roosenboom et al., 2020; Howell et al., 2019; Fisch, 2019; Ernst

and Young, 2018; Chakraborty and Swinney, 2020; PwC, 2019; Deng et al., 2018; Davydiuk et al., 2019), and the demand side, i.e. choices by investors (Fahlenbrach and Frattaroli, 2020; Fisch et al., 2019; Fisch and Momtaz, 2020).⁶ Information providing intermediaries in between supply and demand, however, have received only very little attention, and the literature has largely focused on the governance role of whitepapers provided by the ICO team (Adhami et al., 2018; Giudici and Adhami, 2019; Zhang et al., 2019; Samieifar and Baur, 2020; Florysiak and Schandlbauer, 2019).

To the best of our knowledge, only three existing papers examine ICO analysts (Aggarwal et al., 2019; Bourveau et al., 2019; Lee et al., 2019).⁷ All three papers document that ICOs with higher expert assessments are more successful. Our baseline results confirm this result, but we focus on the striking fact that even among the ICOs with the highest quartile of ratings, more than 50% fail. We show that accounting for the heterogeneity among analysts is important. For example, we exploit the specific feature of the market that ICO analysts do not only provide ratings for ICOs, but may also run their own ICOs. We show that reciprocal ratings are biased, but also that investors discount such reciprocal ratings. We also uncover several other predictors of failure-despite-praise from analysts.

Second, the paper complements the literature on semi-professional analysts in equity markets (Chen et al., 2014; Drake et al., 2017). That literature recognizes that there might be some concerns of conflicts of interest if the semi-professional analyst is holding positions on the stock herself, resulting in a non-objective, distorted analysis (Campbell et al., 2019).⁸ While these studies focus on equity markets in which semi-professional analysts complement the information production of professional analysts, one particular advantage of the ICO market, besides very detailed and structured information, is the absence of professional ana-

⁶There is also a literature on price dynamics of tokens (Cong et al., 2020a,b; Lee and Parlour, 2020; Li and Mann, 2020) as well as studies of asset pricing properties of coins on secondary markets and post-ICO performance (Dittmar and Wu, 2019; Hu et al., 2019; Fisch and Momtaz, 2020; Lyandres et al., 2020). See Li and Mann (2019) for a review of recent literature advances in ICO research.

⁷Momtaz (2020) uses information on ICO analysts, too. However, the paper does not focus on ICO analysts per se, but uses analysts' evaluations as a proxy for one dimension of project quality.

⁸Campbell et al. (2019) use the disclosure of stock positions by non-professional analysts themselves as an indicator of the analyst's position, which might be not reported truthfully.

lysts.⁹ Thus, the market for ICOs provides a unique laboratory setup that allows researchers to examine the conflicts of interest among analysts and their relevance for real outcomes.

Third, the paper adds to the growing literature that determines the relation between machine-generated evaluations and human expert ratings.¹⁰ In addition to human evaluations, machine-generated ratings were set up by many platforms. These ratings do not evaluate the content of an ICO but are based on observable factors such as features of the ICO campaign and the ICO team.¹¹ Importantly, we show that the market considers both ratings, such that machine-generated and human ratings are complements rather than substitutes.

Finally, the paper also contributes to the broader literature on the workings of unregulated markets (Wohlgemuth et al., 2016; Thakor and Merton, 2018; Cascino et al., 2019; Dupont and Karpoff, 2019; Cumming et al., 2020).

The remainder of the paper is organized as follows. Section 2 presents the data and descriptive statistics. Section 3 develops the results. Section 4 concludes.

2 Data and descriptive statistics

2.1 Sample and data source

We collect data on ICOs, ICO ratings and ICO experts from the platform ICObench.com. Our sample consists of 5,384 ICOs (of which 2,378 received at least one rating by an expert)

⁹There are of course many stocks that are not covered by professional analysts. This lack of coverage, however, is by choice of analysts and thus provides already information to the market.

¹⁰For example, Aubry et al. (2019) use data on paintings auctioned to study the accuracy and usefulness of valuations generated by using a pricing algorithm based on neural networks. They conclude that machine learning, while improving the prediction of assets with high price uncertainty, is not ready to replace human judgment completely. Catalini et al. (2018) show that, by using data from a leading startup accelerator, Artificial Intelligence can help humans to screen and evaluate information when there is an information overload.

¹¹Automated algorithms that simply count disclosed information are usually applied. For example, a high number of social media platforms on which an ICO is present or being listed on several rating websites automatically improves the rating for the respective ICO (Boreiko and Vidusso, 2019).

and spans the time period from the first ICOs in August 2015 to February 2020.¹² ICOs in our sample were launched in 127 different countries, of which the USA, Singapore and the UK have the highest market shares.

2.2 ICO analysts

In contrast to regulated financial analysts, there is no certification of ICO analysts. However, analysts have to apply for expert status at a platform, in our case ICObench.com. In particular, to become an expert, one needs to fill in an application form on which one needs to describe the level of experience in crypto assets and the motives to provide ICO ratings. After reviewing these credentials, analysts are confirmed by the platform. The selection is relatively stringent. As of March 2020, the ICObench.com platform hosts more than 111,000 community members of which only 531 have expert status and thus the approval to provide ratings.

ICObench.com ranks the analysts based on several factors like profile completeness and analysts' consistency in contributions to the platform.¹³ This provides an analogy to the widely used all-star rankings of financial analysts. We collect these rankings over time and flag whether an analyst is among the top 30 analysts, i.e., within approximately the top 5 percentile. The dummy variable $StarAnalysts_{ij}$ equals one if analyst i is listed among the top 30 list prior to evaluating ICO j . Interestingly, many of the ICO analysts are involved in one or more ICO campaigns themselves.¹⁴ This dependent network structure of analysts offers a unique setting to investigate the role of human experts in crowdfunding markets (see

¹²The compiled dataset is of comparable size as data used in other empirical ICO studies. For example, Benedetti and Kostovetsky (2018) use a sample of 4,003 ICO campaigns from five websites. Most information was retrieved from ICObench.com and ICOrating.com. Florysiak and Schandlbauer (2019) analyze 4,053 ICOs derived from ICObench.com. Deng et al. (2018) hand-collected a sample of 4,489 ICOs. Recently, Lyandres et al. (2020) cover the largest data set from the ICO universe with 7,514 ICO projects merged from various websites. Note that our sample period also covers the time after the collapse of the ICO market.

¹³The expert weight is calculated based on a profile score, a rating score, a time score, an acceptance score, and a contribution score, see <https://icobench.com/faq> for a detailed description.

¹⁴Note that if ICO analysts become part of the ICO project by advising the team members, they are not allowed to rate their own ICO anymore. We found that 4 analysts have rated the ICO project before becoming an advisory team member.

Section 2.4).

2.3 Ratings

We identify 531 experts on ICObench.com who provide ratings for 2,378 ICOs. On average, each analyst provides a rating for 29.64 ICOs, resulting in a total number of 13,834 ratings. Experts can provide a rating for three dimensions of an ICO, team, vision and product, with each dimension having a score ranging from 1 (poor) to 5 (best). The *TotalRating* score is defined as the sum of these three individual ratings and is an integer in the interval $[3, 15]$ by construction.

For all ratings, we collect the date when the analyst issued the rating. For the main analysis we only use ratings issued before ICO completion (or cancellation). This helps avoid look-ahead bias. However, our findings hold when we include all ratings. Analysts have the opportunity to modify their ratings. In the case that an analyst modified a rating, it is only possible to observe the updated rating score, as well as two dates, i.e., the date of the first rating and the date of the update, but not the full history.¹⁵ Throughout the paper, we consider the modification date as the date for the rating and flag a modified rating by analyst i to ICO j with a dummy variable $Modified_{ij}$.

When issuing a rating, the analyst does not only give a rating score; she usually also justifies her decision by writing a review. We collect all reviews and calculate linguistic measures from these texts. Based on the Loughran and McDonald (2011) dictionaries, we calculate the tone of the language, defined as the difference between positive and negative words to total words, as well as the uncertainty of the language, defined as the count of uncertain words divided by the total words. We further control for the complexity of the review statements, measured by the Gunning (1952) Fog index, which is a function of the number of words per sentence (length of a sentence) and the share of complex words (words

¹⁵In the literature on sell-side analysts, there is a well-documented phenomenon of “walking down” forecasts. The absence of access to the rating history of analysts on ICObench.com prevents us from studying this phenomenon in the ICO context.

with more than two syllables) relative to total words.¹⁶

For some analyses, we aggregate the analyst-ICO information to the ICO level. More precisely, we count the total number of analysts who provided a rating for ICO j in $\#Analysts_j$. We further aggregate all analyst ratings to ICO j in the variable $TotalRating_j$ by averaging all ratings that ICO j received from all analysts that cover this ICO. Finally, we proxy the lack of consensus among analysts that provide a rating for ICO j with $AnalystDispersion_j$, defined as the standard deviation of all ratings for ICO j .

In Figure 2, we present the number of ratings in a given month over time of the newly announced ICOs, the number of ratings by analysts who registered in the same month, as well as the Bitcoin price in US dollar. While the number of new ratings went up hand-in-hand with the number of ICOs to the peak of the Bitcoin price in January 2018, the number of ratings exploded thereafter and has converged only recently again to the number of announced ICOs. Figure 2 further shows that the surging demand for information about crypto assets was met by the increase in the supply of analysts.

[Figure 2 about here]

Figure 3 shows the monthly averaged $TotalRating$ as well as the analysts' rating dispersion, measured by the standard deviation of ratings within an ICO in a given month. We observe that the average total rating of experts is overall very positive with a small decrease in the rating score around the Bitcoin price drop in 2018. Analysts' dispersion is over the sample period at a relative constant level. It only slightly increases around the time when the Bitcoin price was low at the end of 2018, but decreases with a higher Bitcoin price at the end of 2019 again.

[Figure 3 about here]

Complementing the assessment of human experts, many platforms have set up machine-generated ratings. These ratings do not evaluate the quality of the ICO directly but are rather

¹⁶The Gunning (1952) Fog index is defined as $Fog = 0.4 \cdot \left(\frac{TotalWords}{TotalSentences} + \frac{ComplexWords}{TotalWords} \right)$.

based on the availability of information *about* the ICO. The idea is that more transparency indicates higher trustworthiness and quality of the ICO. For all ICOs in our database, we collect the machine-generated rating by ICObench.com, which is called “Benchy”. The Benchy bot provides a higher rating for higher transparency on team and event information. Moreover, Benchy uses factual data such as “presence of the social media links” and “the level of activity on them”, see <https://icobench.com/faq>. Benchy re-evaluates each ICO profile at least once per day and issues a rating ranging between 1 (poor) and 5 (best). Only the most recent evaluation, not the history of Benchy ratings, is observable.

While all ICOs listed on the platform ICObench.com automatically receive a machine-generated rating from the Benchy bot, 2,378 out of 5,384 ICOs listed on this website received a rating by ICO analysts. On average, the ICOs with(out) an analyst rating have a Benchy rating of 3.2(2.7) out of 5.

2.4 Reciprocal ratings

A specific feature of the market is that ICO analysts also participate in ICOs. We identify those experts that are involved in one or several ICO projects by searching each expert’s self-description of experiences and achievements in the ‘About’-section of her profile page on ICObench.com. We show the distribution of ICO projects among analysts in Table 1. Out of the 531 experts in our sample, we find that 329 analysts have been involved in at least one ICO, with some analysts being very active in launching their own ICOs.

[Table 1 about here]

We use this information to flag whether a rating of analyst i to the ICO j is a response to a rating that analyst i received previously from any team member of coin j at any point in time, and generate the indicator variable $ReciprocalRating_{ij}$ as follows:

$$ReciprocalRating_{ij} = \begin{cases} 1, & \exists TotalRating_{j'i'}^{ij} \text{ where } \mathbf{i} \in \Omega_{i'}, j' \in \Omega_j \\ 0, & \text{else} \end{cases}$$

where Ω_j refers to the set of all team members of the ICO j . Table 2 represents a hypothetical illustration of how we define this variable. *ReciprocalRating_{ij}* thus flags whether any member of ICO j has provided a rating of any ICOs that expert i is associated with.¹⁷ Whenever the *ReciprocalRating_{ij}* indicates reciprocity, we additionally identify the level of the reciprocal rating, i.e., the *TotalRating* as well as the three components *TeamRating*, *VisionRating*, and *ProductRating* by any member of ICO j to the ICO that expert i is associated with. The level of the reciprocal rating is labeled *ReceivedTotalRating_{ij}*.

[Table 2 about here]

2.5 ICO outcome variables

We generate a dummy variable *Success*, which takes the value of 1 if the ICO-related coin successfully completes the offering and receives funding. For these ICOs, we collect information on the dollar amount that was raised during the campaign from ICObench.com, ICOmarks.com, tokendata.io and ICOdata.io. Tokens for which we could not find the amount raised nor any success information on the above-mentioned web pages were classified as failed. In total, we identify 1,932 ICOs as being successful.

Figure 4 shows the time trend of successful ICOs. ICOs became popular at the beginning of 2017. While only 29 ICO tokens were on sale until then, the number increased to 1,127 ICOs within one year with around 94 offerings per month and a 53% success rate. The market peaked in 2018 with 3,360 ICOs in total, at a point in time when around 280 ICOs were offered per month with a 33% chance of observing a successful ICO. In 2019, around 64

¹⁷Reciprocal ratings were not directly flagged by ICObench.com, but one can easily obtain the information given the available links to the analyst's associated ICOs and the timeline of the ratings provided on ICObench.com.

ICO offerings were sold per month with an average success rate of 25%. Thus, even after the sharp decline of cryptocurrency prices and the corresponding decline of enthusiasm about ICOs, the flow of ICOs remains ongoing, albeit at a lower level.

[Figure 4 about here]

In addition to measures of success, we collect information that allows us to identify scams, i.e., ICOs that were launched with the intention to defraud investors. To do so, we use the marker ‘Scam or Other Issues’ for dead coins listed on Coinopsy.com, as well as information from Deadcoins.com, a message board where users post about scams. Some of these reported ICOs can also be found in press releases of the U.S. Securities and Exchange Commission (SEC) when the ICO companies are fined for their fraudulent practices.¹⁸ With this (likely conservative) method, 234 ICOs were flagged as scams in our data.

2.6 Forecast errors

Combining the ICO success variable and the analyst rating score allows us to construct, for each rating, an ex-post forecast error measure. As the outcome variable of an ICO is either a success or a failure, we define the forecast error of a rating as the distance to the highest (lowest) possible rating in case of success (failure):

$$ForecastError_{ij} = \begin{cases} 15 - TotalRating_{ij}, & \text{if ICO succeeded} \\ TotalRating_{ij} - 3, & \text{if ICO failed} \end{cases}$$

Thus, if an analyst gives a total rating of 15 to an ICO that was successful, the analyst is fully precise with her rating, resulting in a *ForecastError* measure of 0. If the ICO, however, had failed, the forecast error of this rating would flag a 12, so that $ForecastError \in \{0, \dots, 12\}$.¹⁹

¹⁸See, for example, <https://www.sec.gov/news/press-release/2019-259>.

¹⁹While this *ForecastError* measure is not immediately available for investors on ICObench.com, one can easily view the entire timeline of ratings that an analyst ever provided with a link to detailed information on the rated ICO.

Figure 5 shows the monthly averaged *TotalRating*, the average forecast error and the number of successful ICOs (as a share of total ICOs) over time. In addition, we plot the monthly average forecast error separately for ratings where analysts were too optimistic and too pessimistic, respectively.²⁰ Interestingly, ratings become less precise over time. This is particularly driven by analysts who are too optimistic.

[Figure 5 about here]

In our regression analysis, we use an analyst-specific measure of the forecast error that takes the entire history of an analyst’s ICO-specific *ForecastError_{ij}* into account. We recursively average the *ForecastError_{ij}* of analyst *i* over all her issued ratings up to ICO *j* using an expanding window. We denote this variable *ForecastError_i^j*.

2.7 ICO characteristics

For all ICOs in the sample, we further collect data on the campaign characteristics that have been found in the literature to indicate the perceived quality of an ICO by investors (Amsden and Schweizer, 2018; Burns and Moro, 2018; Howell et al., 2019; Roosenboom et al., 2020). For each characteristic, we generate a dummy variable that flags whether an ICO holds the specific feature. The dummy variable *Presale* equals one if an ICO offers coins at pre-sale stage and zero otherwise. The *Bonus* and *Bounty* dummy equals 1 if there were discounts on the token sale or incentives to boost social media presence. The dummy *MVP* flags the availability of a minimum viable product or whether a product prototype was in place. The dummy *KYC* equals one if investors need to validate their identity by signing up to a whitelist to get access to the token sale,²¹ and the dummy *IEO* indicates the use

²⁰An analyst is too optimistic (pessimistic) if her rating of a failing (successful) ICO was larger (smaller) than 3 (15). Thus, we calculate the monthly average optimistic (pessimistic) forecast error over the lower (upper) cases of the *ForecastError_{ij}* definition.

²¹Note that ICObench.com provides information on two different KYC procedures. One KYC symbol means the identity verification of ICObench.com profiles, the second flags the identification and registration process of investors to receive access to the token sale. We use the second information on KYC throughout the paper.

of a centralized token launch platform provided by a cryptocurrency exchange. In addition to these campaign-specific characteristics, we collect the year-month information of the date when the ICO was launched.

2.8 Descriptive statistics

Table 3 shows descriptive statistics of the key variables of rating and ICO characteristics. A definition of all variables is also provided in Table A1.

[Table 3 about here]

The average *TotalRating* of an analyst in our sample is 11, with a slightly more pessimistic *ProductRating* compared to the other two rating dimensions *TeamRating* and *VisionRating*. 12% of all ratings are flagged as *ReciprocalRating*, and reciprocal ratings are found to be somewhat more positive with an average *ReceivedTotalRating_{ij}* of 13. On the ICO dimension, we observe a success rate of 36%. The most successful ICOs in our sample in terms of dollar amount raised were EOS, Telegram, and Bitfinex. The scam rate is 4.3%. 44% of all ICOs are covered by at least one analyst. Each ICO is on average covered by 2.6 analysts. Sharpay, Truegame and WePower are found to be the ICOs with the largest number of covering analysts (94, 82 and 64 analysts, respectively).

3 Empirical Analysis

Section 3.1 analyzes the determinants of a rating (both quantitative and qualitative) that an analyst gives to an ICO. Section 3.2 in turn considers whether investors take differences in the reliability of analyst ratings into account.

3.1 What determines analyst ratings?

3.1.1 Baseline results

We model the rating of analyst i for ICO j as a function of analyst characteristics, as indicated in the following equation:

$$\begin{aligned} Rating_{ij} = & \beta_0 + \beta_1 \cdot Benchy_j + \beta_2 \cdot StarAnalysts_{ij} + \beta_3 \cdot ForecastError_i^j \\ & + \beta_4 \cdot Modified_{ij} + \beta_5 \cdot X_j + Month_{ij} + \alpha_j + \epsilon_{ij}, \end{aligned} \quad (1)$$

$Rating_{ij}$ denotes interchangeably the rating score that analyst i gives to ICO j for the different rating categories team, vision and product (on a scale from 1–5), and the $TotalRating_{ij}$ score as the sum of the three categories (on a scale from 3–15). The vector X_j contains the ICO campaign characteristics as described in Subsection 2.7. Time trends of ratings are absorbed by $Month_{ij}$ dummies. α_j denotes ICO fixed effects. We allow for a potential serial correlation of ratings within each analyst and within each ICO and employ two-way clustering of standard errors (Cameron et al., 2011) at the analyst and ICO dimension.

[Table 4 about here]

Table 4 summarizes the results of this analysis. Column (1) shows that machine-generated and human expert ratings point on average qualitatively in the same direction, i.e., ICOs with higher machine-generated ratings receive a higher rating score by human analysts on average. Moreover, in the cross-section of analysts, columns (2) and (3), we find a statistically significant negative coefficient on $ForecastError_i^j$, implying that analysts with historically higher forecast errors give on average lower ratings. The negative relationship between the past forecast errors and the rating remains also in the within ICO estimation, as column (4) shows. We also observe that analysts listed on the ranking of top 30 analysts on ICObench.com are on average more critical and issue lower ratings.

Furthermore, in line with the literature, the coefficients of the control variables suggest that analysts take the characteristics of the underlying ICO into their consideration (Deng

et al., 2018; Bourveau et al., 2019; Roosenboom et al., 2020). In particular, we find that ICOs with a pre-sale event, with a KYC feature and an IEO feature receive on average a better rating.

3.1.2 Reciprocal ratings

When ICO analysts issue new ratings, do these ratings depend on ratings that their own affiliated ICOs previously received? To analyze the dependence of new analyst ratings from ratings that their own affiliated ICOs previously received more formally, we run regressions, as specified in the following equation:

$$\begin{aligned} Rating_{ij} = & \beta_0 + \beta_1 \cdot ReciprocalRating_{ij} + Analyst \times Month_{ij} \\ & + ICO \times Month_{ij} + \epsilon_{ij}, \end{aligned} \quad (2)$$

where $ReciprocalRating_{ij}$ indicates a dummy that flags whether analyst i received a rating from a team member of ICO j . We include $Analyst \times Month$ and $ICO \times Month$ dummies to exploit only the analyst and ICO variation within the month of the rating. These fixed effects pick up the variation previously established in Table 4, and they help to rule out that the results were driven by a non-random match between founders of good ICOs that also serve as analysts. For reciprocal ratings, we also analyze whether the level of the prior rating predicts the level of the reciprocal rating.²² We again employ two-way clustering at the analyst and ICO dimension.

[Table 5 about here]

Table 5 shows that indeed ratings contain a reciprocal element. Column (1) indicates a positive association between the total rating an analyst gives to an ICO and the $ReciprocalRating_{ij}$ dummy. More specifically, the total rating score is around 0.25 points

²²We use $Analyst \times Quarter$ and $ICO \times Quarter$ dummies for the analysis because of the restricted sample size.

higher when the analyst is in a position to respond to a prior rating. Additionally, within the sample of reciprocal ratings, column (2) shows that ratings are more positive, the higher the prior received rating was. In other words, analysts reciprocate positive ratings. For example, column (2) shows that each one-unit (one standard deviation) increase for the previous rating leads an analyst to issue an around 0.08 (0.15) higher total rating. Note that this result holds in the within ICO-time and analyst-time dimension, i.e., comparing ratings by two (otherwise) identical analysts, where one analyst previously received a rating by a team member of coin j and the other one did not. This reciprocal rating behavior is similar to the *quid pro quo* between hedge funds and sell-side equity analysts described in Klein et al. (2019).

Columns (3)–(8) analyze the three different rating categories team, vision and product separately. The coefficient for the *ReciprocalRating_{ij}* dummy is positive and significant for all three categories, indicating that analysts give on average a higher rating for the team, the vision and the product of ICO j if they received a rating from any team member of ICO j . However, the actual score is significant only for the team dimension. That is, an analyst issues a higher rating for the team component of ICO j if she received a more favorable team rating from a team member of ICO j . By contrast the scores for vision and product are not significant. These findings are intuitive, as the team category constitutes a relatively “soft factor”. The results also indicate a relatively personal nature of the reciprocity.

3.1.3 Linguistic characteristics of rating reviews

When issuing ratings, analysts often justify the rating scores with written reviews. We next analyze whether more optimistic ratings are special in terms of the linguistic nature of the written review. In the literature on earnings conference calls, the number of words spoken by analysts is used as a proxy for the question difficulty so that analysts who ask lengthier questions are regarded as a more critical (Merkley et al., 2017). We therefore investigate whether the rating score correlates with the length of the written text or with the linguistic

tone of the review. Moreover, we investigate whether the relation between the rating score and the review length and tone differs for reciprocal versus non-reciprocal ratings. This idea follows Cohen et al. (2020), who have documented that biased analysts ask easier questions. We run regressions for the overall sample as well as for reciprocal and non-reciprocal ratings separately as specified in the following equation:

$$\begin{aligned} Linguistic Measure_{ij} = & \beta_0 + \beta_1 \cdot TotalRating_{ij} + Analyst \times Time_{ij} \\ & + ICO \times Time_{ij} + \epsilon_{ij}, \end{aligned} \quad (3)$$

where $Linguistic Measure_{ij}$ indicates interchangeably the length of the rating review measured by the (natural logarithm of the) number of words and the ratio of positive words minus negative words to total words in the review. As before, we employ two-way clustering at the analyst and ICO dimension.

[Table 6 about here]

Table 6 shows the results. In Panel A, column (1), we find a negative relation between the rating score and the length of the review, suggesting that more negative rating scores come with a more detailed explanation. In column (2), we include $Analyst \times Month$ and $ICO \times Month$ dummies to rule out that the results are driven by a non-random match between analyst characteristics (e.g. her mood) and the quality of the rated ICO. For the review tone in Panel B, columns (1) and (2), we find that analysts use more positive terminology when reviewing an ICO that they award a higher rating score.

When investigating whether the relation between the rating score and the review length and tone differs for reciprocal versus non-reciprocal ratings, we find that lower rating scores are justified with even lengthier reviews for reciprocal ratings, with a statistically significant difference to the coefficient for non-reciprocal ratings.²³ The relation between review tone and rating score does not differ markedly between reciprocal and non-reciprocal ratings.

²³Because of the restricted sample size for the sample of reciprocal ratings, we use $Analyst \times Quarter$ and $ICO \times Quarter$ dummies for these analyses.

3.1.4 Order of ratings

The literature on security analysts has documented herding behavior among analysts and has shown that buy or sell recommendations of security analysts have a significant positive influence on the recommendations of the next analysts (Welch, 2000). Thus, reciprocal analysts could not only impact investors with their ratings, but also other analysts in case she covers the ICO at an early stage. We therefore analyze whether analysts provide reciprocal ratings faster and move earlier for ICOs where they issue more positive ratings. To We generate a variable that counts the rank of rating arrival per ICO j from analyst i , i.e., whether analyst i was the first, second, third, ... last analyst that issued a rating for ICO j . We relate the order of the rating coverage to the *ReciprocalRating_{ij}* dummy, as indicated in the following equation:

$$\begin{aligned} OrderRank_{ij} = & \beta_0 + \beta_1 \cdot TotalRating_{ij} + \beta_2 \cdot ReciprocalRating_{ij} + \beta_3 \cdot StarAnalysts_j \\ & + \beta_4 \cdot ForecastError_i^j + Month_{ij} + \alpha_i + \alpha_j + \epsilon_{ij}. \end{aligned} \quad (4)$$

We again absorb any ICO and analyst characteristics with ICO and analyst fixed effects and control for time trends by *Month_{ij}*. As before, we use two-way clustered standard errors at the analyst and ICO dimension.

[Table 7 about here]

The results are shown in Table 7. In line with the literature on the analyst coverage of stocks (Demiroglu and Ryngaert, 2010), we first find that analysts who give favorable ratings tend to issue their rating early. Second, star analysts tend to move first and provide their rating to the same ICO prior to their less experienced peers. Third, reciprocal ratings tend to be issued early on. In particular, in the chronological sequence of ratings given to an ICO j , a reciprocal analyst appears to issue her rating on average 1.3 positions earlier than a non-reciprocal analyst.

3.2 Are ICOs with higher ratings more successful?

So far, we have established several important determinants of ICO analyst ratings, with analyst-specific factors such as the analyst’s experience, prior forecasting ability, and reciprocal status playing a major role in addition to objective differences among the ICOs. We now turn to the question of whether ICOs with higher ratings are indeed more successful. We first establish some baseline results for (unconditional) ICO success, but our main interest is in explaining when investors deviate from the ICO analyst consensus, that is, the ICO success probability conditional on an extreme positive (or negative) rating outcome. We also consider whether the factors that explain such deviations predict scams.

3.2.1 Ratings and ICO success

Table 8 presents some descriptive statistics for the relation between ratings and ICO success.²⁴ Panel A indicates that ICOs are more likely to be successful if that ICO could motivate analysts to provide ratings for it. In Panel B, we tabulate success statistics for groups of the quantitative rating score. The probability of receiving funding and the average dollar amount raised is higher for ICOs with more positive ratings, though the relation is not strictly monotonic.

While these results highlight that on average successful ICOs have higher ratings, there are numerous cases in which ICOs were not successful despite positive ratings or were successful despite negative ratings. To quantify this phenomenon we define for each ICO j a *Disagreement_j* dummy as a conditional success outcome. More precisely, the *Disagreement_j* dummy equals one if (i) the average *TotalRating_j* of an ICO by analysts is greater or equal to 13 but the ICO is not successful, or (ii) the average total rating is less than or equal to 5 and the ICO is successful. In our sample, this *Disagreement_j* dummy is one in 413 of 2,378

²⁴We present some additional descriptive statistics on the relation between campaign characteristics and the ICO success in Table A2.

ICOs with a rating (17%).²⁵

These mismatches between ratings and ICO success do not occur randomly. To illustrate, in Panel C, we tabulate the disagreement dummy against the occurrence of reciprocal ratings. We observe that the ICO outcome does not correspond to what one would expect given the ratings level if there are reciprocal analysts covering the ICO. In particular, we find that ICOs that receive very favorable recommendations fail much more frequently if the reciprocal rating share is positive than if none of the ratings is reciprocal.

[Table 8 about here]

In order to formally analyze ICO success in a regression framework, we first explain the unconditional success of ICO j by characteristics of participating analysts and other variables in a logit regression:

$$\begin{aligned} Success_j = & \beta_0 + \beta_1 \cdot TotalRating_j + \beta_2 \cdot \#Analysts_j + \beta_3 \cdot ReciprocalRatingShare_j \\ & + \beta_4 \cdot StarAnalysts_j + \beta_5 \cdot PreviousRatings_j + \beta_6 \cdot AnalystDispersion_j \\ & + \beta_7 \cdot Benchy_j + \beta_8 \cdot Z_j + \beta_9 \cdot X_j + Month_j + \epsilon_j. \end{aligned} \quad (5)$$

$Success_j$ indicates the success dummy as described in Section 2.²⁶ X_j again represents the controls as in Equation 1. Additionally, we control for linguistic measures with Z_j , which contains the average tone, uncertainty and complexity as well as the length of all rating reviews written on ICO j . We further include a dummy for each month of the sample, $Month_j$ to absorb common time trends to all ICOs. Note that the sample size drops when including the $AnalystDispersion_j$ measure, as it is defined only for ICOs with at least two ratings.

²⁵Note that disagreement most often concerns the case where the rating is high but the ICO fails, and there are only very few cases of successful ICOs with an average poor rating (N=44). We therefore when analyzing disagreement, we focus mainly on these cases.

²⁶In the Appendix, we alternatively use the dollar amount raised during the ICO as a measure of success.

We then run the following logit regression on the ICO level:

$$\begin{aligned}
Disagreement_j = & \beta_0 + \beta_1 \cdot \#Analysts_j + \beta_2 \cdot ReciprocalRatingShare_j \\
& + \beta_3 \cdot StarAnalysts_j + \beta_4 \cdot PreviousRatings_j \\
& + \beta_5 \cdot AnalystDispersion_j + \beta_6 \cdot Benchy_j \\
& + \beta_7 \cdot Z_j + \beta_8 \cdot X_j + Month_j + \epsilon_j,
\end{aligned} \tag{6}$$

where X_j is the same set of controls as in Equation 1 and $Month_j$ dummies absorb common time trends. We again control for some linguistic measures with Z_j , which contains the average tone, uncertainty, complexity and length of all rating reviews written on ICO j .

[Table 9 about here]

[Table 10 about here]

The regressions confirm that ratings are predictive on average. The likelihood of an ICO to be successful is higher if that ICO could motivate analysts to provide ratings for it, once one controls for the Benchy score and a wide variety of ICO characteristics.²⁷ As Table 9 shows, not only the existence of experts' ratings matters, but also the level of the rating. We observe that a more positive $TotalRating_j$ is associated with a higher probability of success.

Reciprocal ratings do not explain the unconditional success outcome of an ICO, but they do correlate significantly with failure conditional on high ratings, as Table 10 shows. Thus, if ICO j receives favorable ratings from many analysts that respond in their rating to any team member of ICO j , the ultimate outcome of the ICO is more likely to deviate from that recommendation. To interpret this result, we note that we control for a wide variety of factors presumably capturing variation in quality of ICOs. It is thus conceivable, though arguably unlikely, that reciprocal ratings are correlated with some additional unobserved variation in

²⁷These results are also in line with the general literature on analysts and rating agencies, which indicates that the market appreciates analyst coverage (Demiroglu and Ryngaert, 2010) or the existence of ratings (Sufi, 2009).

ICO quality. The second, not mutually exclusive, interpretation is that investors trust ICOs with more potentially biased ratings less.

Similar patterns emerge for the linguistic measures of the rating. They do not predict ICO success per se (at least once controlling for the quantitative rating). However, that does not mean that they contain no information. Table 10 shows that highly-rated ICOs are more likely to fail the more positive the tone and the more complex the language is. Similarly, ICO failure despite high average ratings more frequently occurs if the analysts were more positive in ratings prior to the rating of ICO j .

Table 9 suggests that star analyst coverage is not predictive for ICO success. However, Table 10 reveals that highly rated ICOs less frequently fail when they are covered by many star analysts.

Table 9 further shows that the machine-generated rating Benchy, too, is predictive. We find that an ICO is on average more likely to be successful the higher the machine-generated rating, that is, the more information on the ICO is publicly available. Importantly, the human ratings remain significant determinants of success throughout, indicating that the two rating types provide different pieces of information for investors.

Finally, analyst dispersion, too, is relevant for ICO success only if the average view of analysts is very positive. Interestingly, and perhaps initially surprisingly, when dispersion of ratings among analysts is higher, this makes it less likely that the ICO fails. Intuitively, the combination of high average ratings and high dispersion occurs when there are several extremely positive and some negative views. It appears that the very positive ratings then carry the day. This is similar in spirit to the apparent anomaly that stocks with high dispersion of analyst opinions have high prices and, thus, lower future returns (Diether et al., 2002).²⁸

Moreover, we observe interesting results in Table 9 for the two relatively new features

²⁸In equity markets, this interpretation of analyst dispersion has been challenged. For example, Avramov et al. (2009) show that the analyst dispersion anomaly is driven by a small fraction of firms with very high credit risk.

of ICOs that have not received attention in the literature so far: MVPs and IEOs. While the use of crypto-exchange launchpads for Initial Exchange Offerings (IEOs) positively correlates with the two success variables, the existence of a minimum viable product (MVP) does not lead to a higher success probability. Somewhat surprisingly, ICOs with an MVP feature a lower probability of success and were able to attract only a lower dollar amount of funding. This unexpected result might be due to a non-regulated definition of minimum viable products.²⁹

3.2.2 Ratings and ICO scams

We have established that analyst ratings help predict ICO success, but that reciprocal ratings tend to be disregarded by investors. Does the latter result occur because ICOs with a higher fraction of reciprocal ratings are more likely to be fraudulent? To answer, we rerun the regression as outlined in Equation 5, but replace the success dummy with a dummy that equals one if the ICO was detected to intentionally defraud investors.

[Table 11 about here]

As Table 11 shows, we observe no correlation between the share of reciprocal analysts and fraudulent ICOs. Also, neither the level of machine-generated ratings nor the level of human analyst ratings helps to identify fraudulent ICOs. However, it still pays for investors to consider the human analyst assessments. In particular, ICOs with more dispersion among analysts both in the quantitative and in the qualitative rating tend to be fraudulent.

4 Conclusion

The merging of new technologies and financial markets (FinTech) holds great promise. One relatively recent phenomenon in this space is the opportunity for new ventures to engage in

²⁹For example, drafts of codes on GitHub.com that are open to a discussion by other GitHub users were classified as MVP.

a new form of financing, Initial Coin Offerings (ICOs). However, the problem of asymmetric information looms large in these markets. This paper studies information intermediaries, human experts, that may help ameliorate this asymmetric information problem.

While the ICO setting is interesting in its own right, ICO analysts show many interesting parallels to equity analysts or rating agencies. Particularly noteworthy are potential conflicts of interest, and how investors interpret those. For example, we document that an ICO analyst i , when rating an ICO j , tends to issue a rating that depends on the rating that their own affiliated ICO had previously received from team members of ICO j . However, there is a higher probability that an ICO fails even with very favorable ratings when more of those ratings are reciprocal. Moreover, such disagreement between investors and analysts is also more likely in ICOs with a large share of ratings by analysts with a history of very positive ratings.

Thus, while the prior literature has shown that average ratings by human experts predict the success of an ICO campaign (over and above machine-generated ratings), our key result is that an understanding of ICO success requires going beyond averages and instead studying the detailed characteristics of the ratings and those who provide them. After all, even among the most highly rated ICOs, failure is frequent. Reciprocal ratings and highly positive reviews may be correlates of problems of highly rated ICOs not reflected in the many ICO characteristics we control for; alternatively, it is possible that investors trust ICOs with more reciprocal and optimistic analysts less despite them being worth funding. Either way, the findings suggest that investors do not blindly pile capital into highly rated ICOs. Such a differentiated approach of investors is a precondition for the ICO market to fulfill its allocative role in society.

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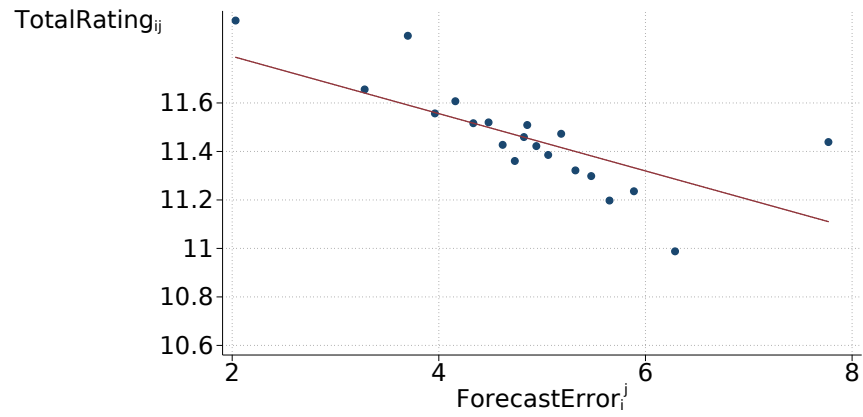
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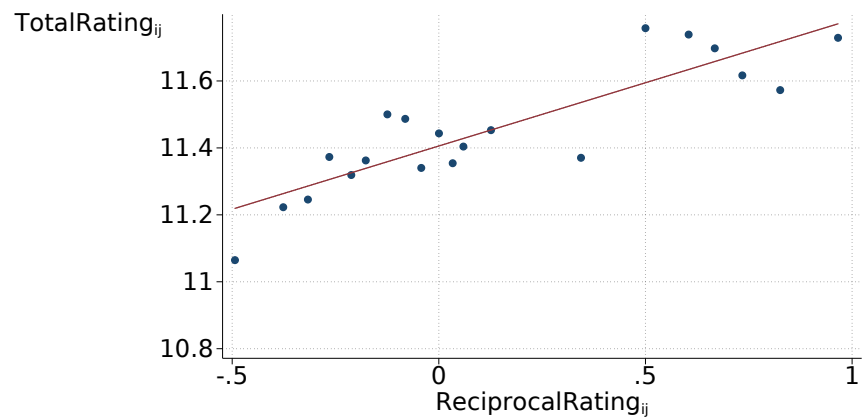
Figure 1: Summary of the main results.

The figure shows binned scatter plots summarizing the main results. All panels use within ICO variation, i.e., ICO fixed effects are absorbed for binned scatter plots based on analyst variation (Panel (a)–(b)). All variables are defined in Table A1.

(a) Optimistic analysts become more careful



(b) Reciprocal ratings are more favorable



(c) Reciprocal ratings are worse predictors of ICO success.

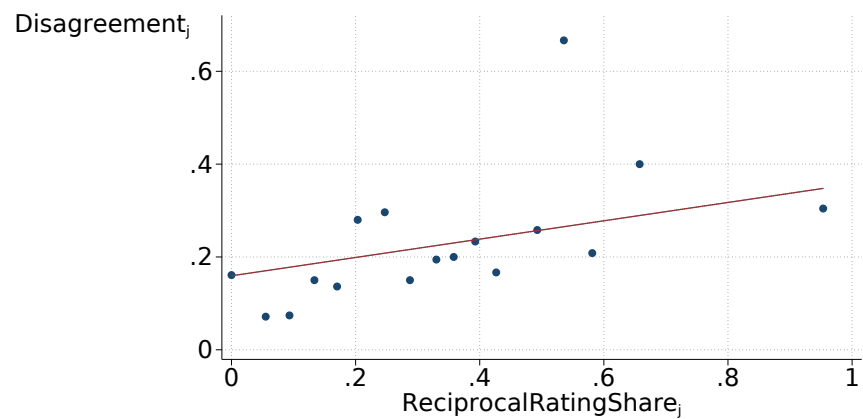


Figure 2: Number of ratings in a month and the Bitcoin price in \$.

This figure presents the number of ratings in a given month over time of the newly announced ICOs, the number of ratings by analysts who registered in the same month, as well as the Bitcoin price in \$.

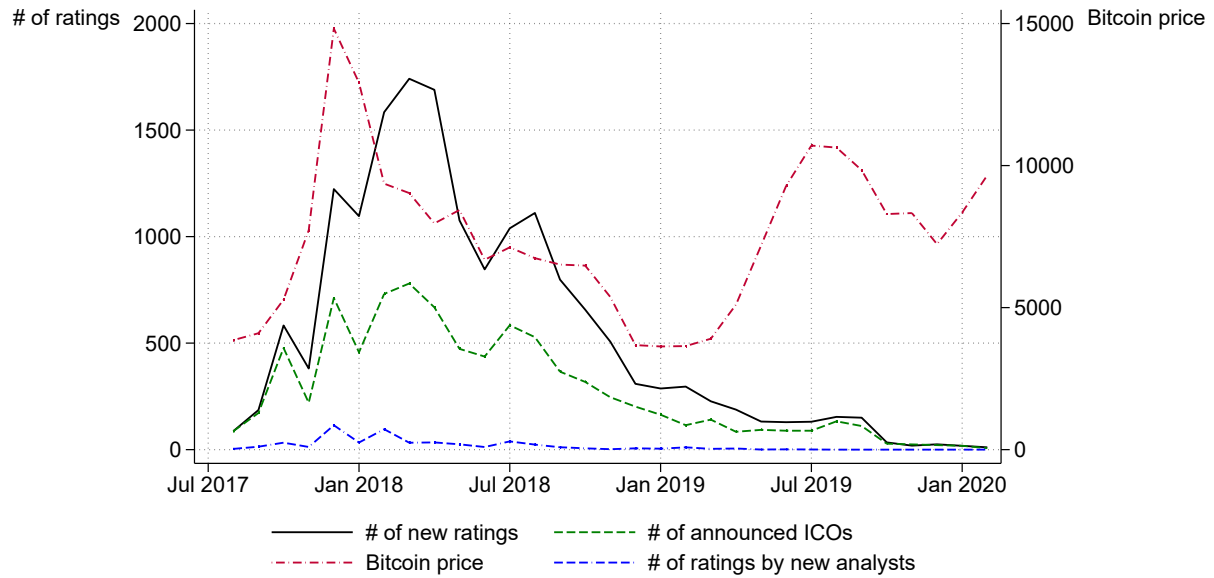


Figure 3: ICO analyst ratings and rating dispersion over time.

This figure plots average total rating and analysts' rating dispersion (left axis) as well as the Bitcoin price in \$ (right axis).

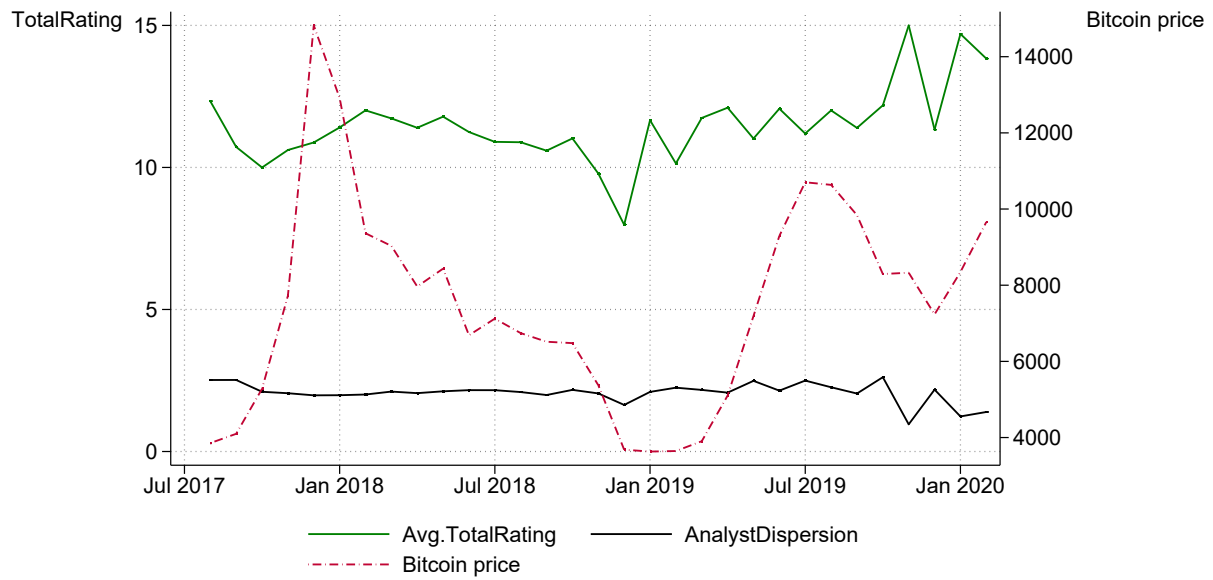


Figure 4: Successful and unsuccessful ICOs over time.

The figure shows the number of ICOs over time, distinguishing between successful and failed ICOs. An ICO is labeled successful if the related coin successfully completes the offering and receives funding. In total, we identify 5,384 ICOs of which 1,932 ICOs succeeded.

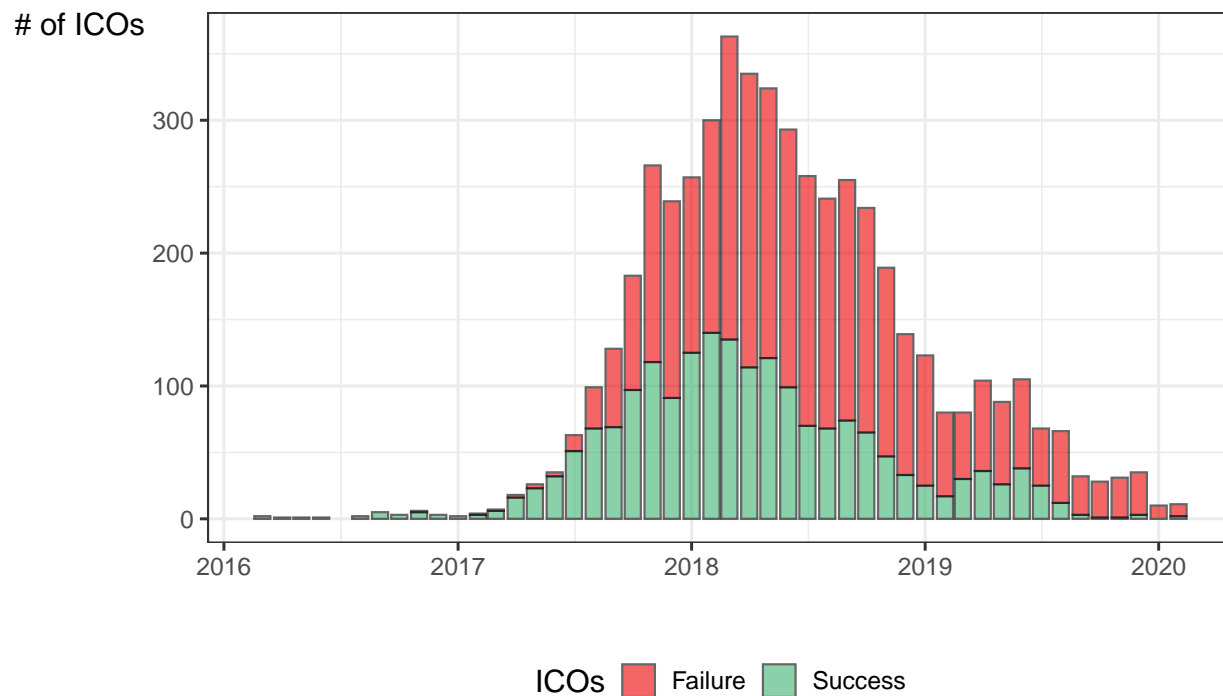


Figure 5: Forecast error over time.

This figure shows the average forecast error and the number of successful ICOs (as a share of total ICOs) in a given month. The average forecast error is further split into $ForecastErrorOptimistic_i$ and $ForecastErrorPessimistic_i$ to capture the monthly averaged forecast error separately for the ratings when the analyst was too optimistic and pessimistic, respectively.

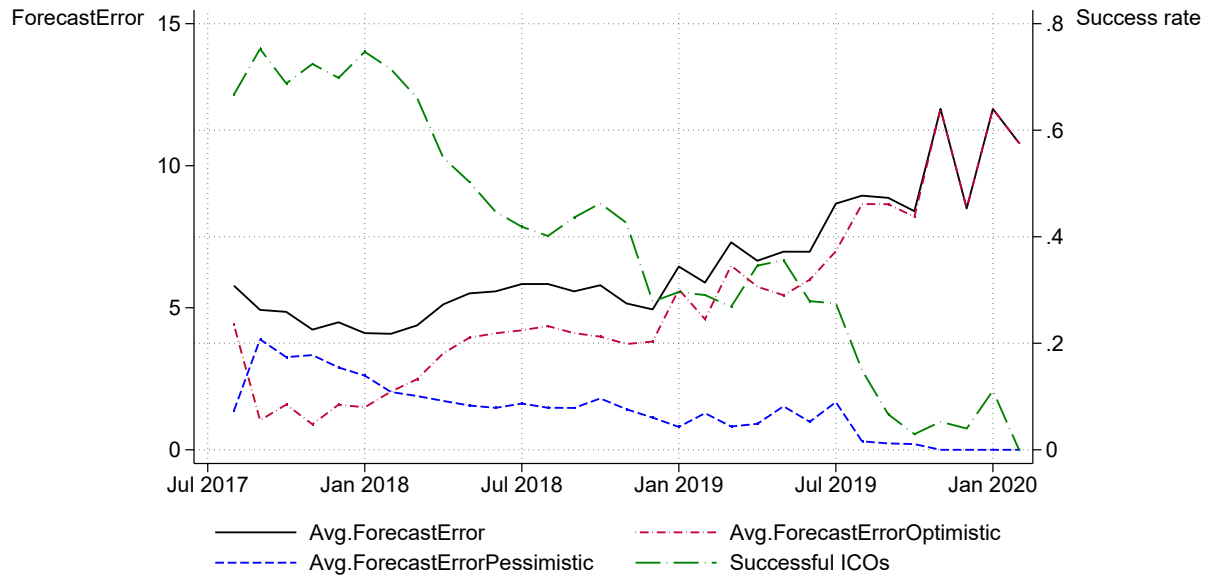


Table 1: ICO affiliation of analysts from the platform ICObench.com.

This table tabulates the distribution of ICO projects among analysts. The total number of analysts in our sample is 531. The List of associated ICOs for each analyst is available on their webpage in ICObench.com

Number of associated ICOs	Count
0	230
1	127
2	52
3	29
4	24
5	15
6	9
7	13
8	3
9	8
≥ 10	49
Total number of analysts	531

Table 2: ICO analyst networks: An example.

This table presents a hypothetical example of our data set. In Panel A, we show the team members of the three ICOs in the sample, namely, “A-Tokens” where Adam and Ashley are among the team members, “Bethereum” where the team includes Barbara and Benjamin, and “CryptoPay” with Cora and Chris in the team. In Panel B, we outline a hypothetical rating history. For example, in October 2017, Ashley (member of A-Tokens) provides a rating of 12 for Bethereum. In December 2017, Chris (member of CryptoPay) provides a rating of 15 for Bethereum. For this rating, we set *ReciprocalRating* equal to one because, in a month before that, in November 2017, Benjamin (member of Bethereum) gave a rating of 14 for CryptoPay, with which Chris is affiliated. Hence, we consider the rating given in December 2017 as a reply to the rating received in November 2017.

A. ICOs and members:

A-Tokens	Bethereum	CryptoPay	...
Adam Ashley	Barbara Benjamin	Cora Chris	

B. Ratings:

Date	Analyst	provides a rating for:	TotalRating	ReciprocalRating	ReceivedTotalRating if <i>ReciprocalRating</i> = 1
1)Oct 2017	Ashley	Bethereum	12	0	-
2)Nov 2017	Benjamin	CryptoPay	14	0	-
3)Dec 2017	Chris	Bethereum	15	1	14
4)Jan 2018	Adam	CryptoPay	9	0	-
...					

Table 3: Descriptive statistics.

This table shows descriptive statistics of the variables used in the analyses. Within each panel, the variables are sorted alphabetically. The sample consists of 5,384 ICOs listed in ICObench.com, of which, 2,378 received in total 13,834 ratings. All variables are defined in Table A1.

	N	Min	P25	Mean	P50	P75	Max	Std. Dev.
<i>A.Rating characteristics</i>								
<i>ForecastError_i^j</i>	12,460	0	4.1	4.8	4.8	5.6	12	1.5
<i>Modified_{ij}</i>	13,834	0	0	.13	0	0	1	.33
<i>OrderRank_{ij}</i>	7,639	1	6	14	11	18	94	12
<i>ProductRating_{ij}</i>	13,834	1	3	3.6	4	5	5	1.1
<i>ReceivedProductRating_{ij}</i>	1,754	1	4	4.1	4	5	5	.74
<i>ReceivedTeamRating_{ij}</i>	1,754	1	4	4.3	4	5	5	.67
<i>ReceivedTotalRating_{ij}</i>	1,754	3	12	13	12	14	15	1.8
<i>ReceivedVisionRating_{ij}</i>	1,754	1	4	4.2	4	5	5	.7
<i>ReciprocalRating_{ij}</i>	13,834	0	0	.13	0	0	1	.33
<i>ReviewLength_{ij}</i>	9,165	1.1	3.4	3.8	3.9	4.3	7.9	.97
<i>ReviewTone_{ij}</i>	9,165	-.75	-.043	-.014	-.0086	.018	.67	.075
<i>StarAnalyst_{ij}</i>	13,834	0	0	.27	0	1	1	.44
<i>TeamRating_{ij}</i>	13,834	1	3	3.9	4	5	5	1.1
<i>TotalRating_{ij}</i>	13,834	3	10	11	12	14	15	3
<i>VisionRating_{ij}</i>	13,834	1	3	3.9	4	5	5	1.1
<i>B.ICO characteristics</i>								
<i>AmountRaised_j</i>	5,384	0	0	5.4	0	14	22	7.3
<i>AnalystDispersion_j</i>	1,638	0	1.2	2	1.9	2.6	8.5	1.3
<i>Benchy_j</i>	5,384	.1	2.4	2.9	2.9	3.5	5	.75
<i>Bitcointalk_j</i>	5,384	0	0	.57	1	1	1	.5
<i>Bonus_j</i>	5,384	0	0	.14	0	0	1	.35
<i>Bounty_j</i>	5,384	0	0	.28	0	1	1	.45
<i>Disagreement_j</i>	2,378	0	0	.17	0	0	1	.38
<i>Duration_j</i>	5,292	0	1	1.7	1	2	121	2.6
<i>Facebook_j</i>	5,384	0	1	.78	1	1	1	.41
<i>ForecastError_j</i>	2,322	0	4.3	5	4.9	5.7	11	1.1
<i>IEO_j</i>	5,384	0	0	.051	0	0	1	.22
<i>KYC_j</i>	5,384	0	0	.48	0	1	1	.5
<i>MVP_j</i>	5,384	0	0	.19	0	0	1	.4
<i>Presale_j</i>	5,384	0	0	.52	1	1	1	.5
<i>PreviousRatings_j</i>	2,322	3	11	11	11	12	15	1.4
<i>ReciprocalRatingShare_j</i>	2,378	0	0	.072	0	0	1	.19
<i>RetentionRatio_j</i>	4,238	0	30	46	45	60	100	21
<i>ReviewComplexity_j</i>	1,883	4.6	11	12	12	14	59	3.2
<i>ReviewLength_j</i>	1,883	1.1	3.6	4	4	4.5	7.3	.81
<i>ReviewToneDispersion_j</i>	1,240	0	.03	.057	.046	.073	.55	.046
<i>ReviewTone_j</i>	1,883	-.67	-.04	-.02	-.015	.003	.29	.056
<i>ReviewUncertainty_j</i>	1,883	0	0	.016	.011	.021	.33	.022
<i>Scam_j</i>	5,384	0	0	.043	0	0	1	.2
<i>StarAnalysts_j</i>	2,378	0	0	.31	.22	.5	1	.34
<i>Success_j</i>	5,384	0	0	.36	0	1	1	.48
<i>WhitePaper_j</i>	5,384	0	1	.88	1	1	1	.32
<i># Analysts_j</i>	5,384	0	0	2.6	0	2	94	6.1

Table 4: Rating determinants.

This table presents linear regression results for Equation 1. The dependent variable is the total rating score that an ICO received by an analyst. All variables are defined in Table A1. t -statistics are given in parentheses. The underlying standard errors are clustered on the ICO and analyst level and are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. variable:	<i>TotalRating_{ij}</i>				
	(1)	(2)	(3)	(4)	(5)
<i>Bench_{yj}</i>	1.518*** (10.43)	1.598*** (11.35)		0.933*** (6.68)	
<i>StarAnalyst_{ij}</i>		-0.720*** (-3.58)	-0.697*** (-3.41)	-0.698*** (-3.45)	-0.454** (-2.47)
<i>ForecastError_i^j</i>		-0.158*** (-3.61)	-0.164*** (-3.99)	-0.170*** (-4.31)	-0.081** (-2.31)
<i>MVP_j</i>			0.308** (2.10)	-0.019 (-0.13)	
<i>IEO_j</i>			0.761*** (3.50)	0.587** (2.53)	
<i>Presale_j</i>			0.276** (2.24)	0.222* (1.87)	
<i>KYC_j</i>			0.859*** (5.13)	0.527*** (3.25)	
<i>Bounty_j</i>			0.250* (1.92)	0.193 (1.56)	
<i>Bonus_j</i>			0.171 (1.41)	0.164 (1.42)	
<i>RetentionRatio_j</i>			0.006* (1.94)	0.004 (1.49)	
<i>Duration_j</i>			-0.018 (-0.43)	-0.041 (-1.23)	
<i>WhitePaper_j</i>			-0.861** (-2.53)	-0.423 (-1.25)	
<i>Bitcointalk_j</i>			0.187 (0.98)	0.019 (0.10)	
<i>Facebook_j</i>			0.800** (2.39)	0.557 (1.64)	
Observations	13834	12460	11114	11114	11698
R^2	0.121	0.146	0.069	0.096	0.528
MonthRating Dummies	No	No	No	No	Yes
ICO FE	No	No	No	No	Yes

Table 5: Reciprocal ratings.

This table presents linear regression results for Equation 2. The dependent variable is the total rating score that an ICO received by an analyst. In columns (1), (3), (5) and (7), regressions include all the ratings in the sample. In columns (2), (4), (6) and (8), we restrict the sample to the reciprocal ratings (*ReciprocalRating* = 1). All specifications include *Analyst* and *ICO* fixed effects multiplied by dummies for the time of the rating (i.e., *Analyst* \times *Month* and *ICO* \times *Month* fixed effects in odd columns and *Analyst* \times *Quarter* and *ICO* \times *Quarter* fixed effects in even columns). All variables are defined in Table A1. *t*-statistics are given in parentheses. The underlying standard errors are clustered on the ICO and analyst level and are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. variable:	<i>TotalRating_{ij}</i>		<i>TeamRating_{ij}</i>		<i>VisionRating_{ij}</i>		<i>ProductRating_{ij}</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>ReciprocalRating_{ij}</i>	0.252** (2.47)		0.062* (1.80)		0.074* (1.76)		0.117*** (2.85)	
<i>ReceivedTotalRating_{ij}</i>		0.080* (1.74)						
<i>ReceivedTeamRating_{ij}</i>				0.117*** (3.13)				
<i>ReceivedVisionRating_{ij}</i>						0.065 (1.14)		
<i>ReceivedProductRating_{ij}</i>								0.000 (0.01)
<i>Modified_{ij}</i>		-1.114*** (-3.54)		-0.381*** (-3.02)		-0.298** (-2.53)		-0.427*** (-3.46)
Observations	10354	1302	10354	1302	10354	1302	10354	1302
<i>R</i> ²	0.757	0.682	0.717	0.621	0.692	0.666	0.708	0.647
<i>Analyst</i> \times <i>Time_{ij}</i> <i>Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>ICO</i> \times <i>Time_{ij}</i> <i>Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Linguistic nature of rating reviews.

This table presents linear regression results for Equation 3. The dependent variable in Panel A is *ReviewLength*, defined as the natural logarithm of the total number of words in a rating review, and in Panel B *ReviewTone*, defined as the ratio of positive words minus negative words to total words in the rating review. We restrict the sample to reciprocal ratings (*ReciprocalRating* = 1) in column (3) and to non-reciprocal ratings (*ReciprocalRating* = 0) in column (4). We include *Analyst* and *ICO* fixed effects multiplied by dummies for the month of ratings (i.e., *Analyst* \times *Month* and *ICO* \times *Month* fixed effects) in column (2). As in Table 5, we can only include the interaction of ICO (analyst) and quarter dummies when restricting the sample to reciprocal ratings in column (3), i.e., *Analyst* \times *Quarter* and *ICO* \times *Quarter* fixed effects. In order to compare the coefficients for reciprocal and non-reciprocal ratings, we also include *Analyst* \times *Quarter* and *ICO* \times *Quarter* fixed effects in column (4). All variables are defined in Table A1. *t*-statistics are given in parentheses. The underlying standard errors are clustered on the ICO and analyst level and are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. Variable:	Panel A			
	<i>ReviewLength_{ij}</i>			
	(1)	(2)	(3)	(4)
<i>TotalRating_{ij}</i>	-0.056*** (-5.42)	-0.041*** (-5.41)	-0.090*** (-5.10)	-0.036*** (-5.37)
Observations	9165	6206	866	6119
<i>R</i> ²	0.033	0.825	0.800	0.786
<i>Analyst</i> \times <i>Time_{ij}</i> Dummies	No	Yes	Yes	Yes
<i>ICO</i> \times <i>Time_{ij}</i> Dummies	No	Yes	Yes	Yes

Dep. Variable:	Panel B			
	<i>ReviewTone_{ij}</i>			
	(1)	(2)	(3)	(4)
<i>TotalRating_{ij}</i>	0.006*** (10.09)	0.006*** (7.51)	0.009*** (3.34)	0.005*** (8.17)
Observations	9165	6206	866	6119
<i>R</i> ²	0.062	0.537	0.522	0.477
<i>Analyst</i> \times <i>Time_{ij}</i> Dummies	No	Yes	Yes	Yes
<i>ICO</i> \times <i>Time_{ij}</i> Dummies	No	Yes	Yes	Yes

Table 7: Order of rating issuance.

This table presents linear regression results for Equation 4. The dependent variable is the order rank of the rating for an ICO. A lower value of the variable indicates that analyst i issued the rating for ICO j earlier. All specifications include month dummies of the analyst rating. The sample is limited to the ICOs with more than ten ratings. All variables are defined in Table A1. t -statistics are given in parentheses. The underlying standard errors are clustered on the ICO and analyst level and are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. variable:	<i>OrderRank_{ij}</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>TotalRating_{ij}</i>	-0.104 (-1.65)		-0.085 (-1.36)	-0.182*** (-2.82)		-0.177*** (-2.75)
<i>ReciprocalRating_{ij}</i>		-1.764*** (-3.17)	-1.725*** (-3.08)		-1.249** (-2.56)	-1.213** (-2.48)
<i>StarAnalyst_{ij}</i>	-1.109*** (-3.00)	-0.855*** (-2.60)	-0.886*** (-2.69)			
<i>ForecastError_i^j</i>	-0.028 (-0.32)	-0.027 (-0.31)	-0.036 (-0.42)	-0.130 (-1.18)	-0.133 (-1.22)	-0.122 (-1.12)
Observations	6829	6829	6829	6767	6767	6767
R^2	0.672	0.674	0.674	0.709	0.709	0.709
MonthRating Dummies	Yes	Yes	Yes	Yes	Yes	Yes
ICO FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	No	No	Yes	Yes	Yes

Table 8: Ratings and ICO success: Descriptive evidence.

This table presents descriptive statistics for the relation between ratings and ICO success. Panel A shows the success of ICOs that were or were not covered by human analysts. Panel B links ICO success to the quantitative rating score. Panel C shows investor disagreement for ICOs with or without any reciprocal rating.

Panel A

Analyst Coverage	Total #	Funded #	in %	AmountRaised avg. in \$	Ln(AmountRaised) avg. in \$
No	3,006	899	29.91	18,600,000	4.40
Yes	2,378	1,033	43.44	12,700,000	6.60
Total	5,384	1,932	35.88	15,500,000	5.38

Panel B

TotalRating Score	Total #	Funded #	in %	AmountRaised avg. in \$	Ln(AmountRaised) avg. in \$
3	217	52	23.96	20,600,000	3.38
4–6	253	55	21.74	6,006,378	3.09
7–9	487	175	35.93	14,200,000	5.54
10–12	1,076	549	51.02	12,100,000	7.77
13–15	767	405	52.80	31,200,000	8.27

Panel C

Reciprocal Rating	Total #	Disagreement #	in %	Disagreement with Avg. Rating ≥ 13 #	in %
Yes*	415	97	23.37	96	49.23
No**	1,963	316	16.10	272	23.65

* $ReciprocalRatingShare_j > 0$

** $ReciprocalRatingShare_j = 0$

Table 9: Ratings and ICO success.

This table presents marginal effects of logit regressions for Equation 5. The dependent variable is the *Success* dummy. The controls for which coefficients are not shown for space reasons include dummies for pre-sale, bonus/bounty options, *KYC*, retention ratio, duration, bitcointalk, and facebook. All specifications include month dummies of the ICOs. All variables are defined in Table A1. *t*-statistics are given in parentheses. The underlying standard errors are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. variable:	<i>Success_j</i>			
	(1)	(2)	(3)	(4)
<i>TotalRating_j</i>	0.110*** (5.47)	0.130*** (3.99)	0.116*** (2.84)	0.073* (1.67)
<i># Analysts_j</i>	0.026*** (3.51)	0.020** (2.56)	0.038*** (4.15)	0.026*** (2.82)
<i>StarAnalysts_j</i>		-0.105 (-0.40)	-0.060 (-0.17)	-0.157 (-0.43)
<i>ReciprocalRatingShare_j</i>		-0.110 (-0.35)	0.084 (0.24)	-0.098 (-0.27)
<i>PreviousRatings_j</i>		-0.020 (-0.27)	-0.032 (-0.38)	-0.075 (-0.83)
<i>AnalystDispersion_j</i>		-0.003 (-0.07)	-0.017 (-0.29)	-0.067 (-1.08)
<i>Bench_j</i>	0.682*** (8.15)	0.774*** (7.15)		0.886*** (5.59)
<i>ReviewToneDispersion_j</i>			-0.402 (-0.20)	-0.603 (-0.29)
<i>ReviewTone_j</i>			1.044 (0.56)	1.133 (0.57)
<i>ReviewUncertainty_j</i>			-4.754 (-0.96)	-5.577 (-1.09)
<i>ReviewComplexity_j</i>			0.002 (0.06)	0.002 (0.05)
<i>ReviewLength_j</i>			0.029 (0.23)	0.011 (0.08)
<i>MVP_j</i>			-0.127 (-0.75)	-0.385** (-2.17)
<i>IEO_j</i>			0.867*** (2.91)	0.786** (2.55)
Observations	2372	1612	1111	1111
Pseudo R^2	0.146	0.154	0.161	0.185
Controls	No	No	Yes	Yes
<i>Month_j Dummies</i>	Yes	Yes	Yes	Yes

Table 10: ICO outcomes that deviate from what ratings predict.

This table presents marginal effects of logit regressions for Equation 6. The dependent variable is the *Disagreement* dummy which equals one if (i) analysts give an average $TotalRating_j \geq 13$ and the ICO fails, or if (ii) analysts give an average $TotalRating_j \leq 5$ and the ICO succeeds. In columns (3) and (4), observations restricted to the case (i). All analyst variables are average values over all analysts that provide a rating for the ICO. The controls for which coefficients are not shown for space reasons include dummies for pre-sale, bonus/bounty options, *KYC*, retention ratio, duration, bitcointalk, and facebook. All specifications include month dummies of the ICOs. All variables are defined in Table A1. *t*-statistics are given in parentheses. The underlying standard errors are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. variable:	<i>Disagreement_j</i>			
	(1)	(2)	(3)	(4)
<i># Analysts_j</i>	0.007 (0.83)	0.008 (0.86)	0.042*** (2.99)	0.057*** (3.34)
<i>StarAnalysts_j</i>	-0.762** (-2.11)	-0.623 (-1.57)	-1.346*** (-3.01)	-0.916* (-1.89)
<i>ReciprocalRatingShare_j</i>	1.028*** (2.80)	0.869** (2.15)	2.033*** (4.34)	1.810*** (3.29)
<i>PreviousRatings_j</i>	0.295*** (3.24)	0.216** (2.14)	0.532*** (4.25)	0.461*** (3.43)
<i>AnalystDispersion_j</i>	-0.458*** (-7.07)	-0.468*** (-6.31)	-0.678*** (-7.67)	-0.729*** (-7.12)
<i>Bench_j</i>	0.055 (0.48)	-0.160 (-1.07)	0.597*** (3.76)	0.264 (1.21)
<i>ReviewTone_j</i>		8.438*** (4.02)		17.717*** (4.26)
<i>ReviewUncertainty_j</i>		-0.008 (-0.00)		-9.731 (-0.98)
<i>ReviewComplexity_j</i>		0.059* (1.72)		0.135*** (3.04)
<i>ReviewLength_j</i>		-0.062 (-0.42)		-0.009 (-0.04)
<i>MVP_j</i>		0.104 (0.51)		0.005 (0.02)
<i>IEO_j</i>		-0.745** (-2.37)		-0.564 (-1.27)
Observations	1615	1222	776	640
Pseudo R^2	0.194	0.198	0.263	0.307
Controls	No	Yes	No	Yes
<i>Month_j Dummies</i>	Yes	Yes	Yes	Yes

Table 11: ICO scams.

This table presents marginal effects of logit regressions analogous to Equation 5, with the dependent variable being the *Scam* dummy. The controls for which coefficients are not shown for space reasons include dummies for pre-sale, bonus/bounty options, *KYC*, retention ratio, duration, bitcointalk, and facebook. All specifications include month dummies of the ICOs. All variables are defined in Table A1. *t*-statistics are given in parentheses. The underlying standard errors are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. variable:	<i>Scam_j</i>			
	(1)	(2)	(3)	(4)
<i>TotalRating_j</i>	0.059 (1.31)	-0.009 (-0.13)	0.062 (0.53)	0.070 (0.59)
<i># Analysts_j</i>	0.027*** (2.82)	0.027*** (2.73)	0.027* (1.80)	0.028* (1.85)
<i>StarAnalysts_j</i>		-0.272 (-0.42)	-0.936 (-0.94)	-0.904 (-0.89)
<i>ReciprocalRatingShare_j</i>		-0.157 (-0.22)	-0.081 (-0.09)	-0.052 (-0.06)
<i>PreviousRatings_j</i>		0.248 (1.61)	0.506** (2.02)	0.505** (2.03)
<i>AnalystDispersion_j</i>		0.274** (2.34)	0.570*** (4.15)	0.568*** (4.17)
<i>Benchy_j</i>	-0.217 (-1.20)	-0.386** (-2.05)		-0.174 (-0.49)
<i>ReviewToneDispersion_j</i>			6.342** (2.17)	6.194** (2.10)
<i>ReviewTone_j</i>			-1.510 (-0.43)	-1.725 (-0.49)
<i>ReviewUncertainty_j</i>			-8.875 (-1.03)	-8.811 (-1.02)
<i>ReviewComplexity_j</i>			-0.064 (-1.02)	-0.064 (-1.04)
<i>ReviewLength_j</i>			-0.151 (-0.46)	-0.146 (-0.45)
<i>MVP_j</i>			0.556 (1.48)	0.600 (1.57)
<i>IEO_j</i>			-0.471 (-0.62)	-0.472 (-0.64)
Observations	2127	1466	966	966
Pseudo R^2	0.057	0.066	0.188	0.189
Controls	No	No	Yes	Yes
<i>Month_j Dummies</i>	Yes	Yes	Yes	Yes

Appendix

Table A1: Definition of variables.

Variable	Definition
$\#Analysts_j$	Number of analysts that provide a rating for an ICO.
$AmountRaised_j$	Natural logarithm of one plus \$ amount raised by an ICO.
$AnalystDispersion_j$	Standard deviation of ratings within an ICO.
$Benchy_j$	Machine-generated rating created by ICObench.com.
$Bitcointalk_j$	Dummy variable that equals one if the ICO is discussed on the forum bitcointalk.org.
$Bonus_j$	Dummy variable that equals one for ICOs with a quantity discount at the token sale or a discount program for early-bird investors.
$Bounty_j$	Dummy variable that equals one for ICOs with incentives to promote social media presence.
$Disagreement_j$	Dummy variable that equals one if (i) on average analysts give a buy recommendation ($TotalRating_j \geq 13$) and the ICO fails, or if (ii) on average analysts give a sell recommendation ($TotalRating_j \leq 5$) and the ICO succeeds.
$Duration_j$	The time span between the sale start and end of an ICO (measured in months).
$Facebook_j$	Dummy variable that equals one if an ICO has a Facebook page.
$ForecastError_{ij}$	The distance of the total rating from the highest (lowest) possible rating in the case of ICO success (failure).
$ForecastErrorOptimistic_i$	The distance of the highest possible rating score to the actual total rating of analyst i , defined as $15 - RatingTotal$, if the ICO was not successful, and averaged over all ICOs j .
$ForecastErrorPessimistic_i$	The distance of the total rating of analyst i to the lowest possible rating score, defined as $RatingTotal - 3$, if the ICO was successful, and averaged over all ICOs j .
$ForecastError_i^j$	A recursive average of all previous forecast errors for any analyst i up to the rating issuance date for ICO j .
$ForecastError_j$	A recursive average of the previous forecast errors of all analysts covering ICO j up to the rating issuance date.
IEO_j	Dummy variable that equals one for ICOs conducted on the platform of a cryptocurrency exchange (Initial Exchange Offerings).

KYC_j	Dummy variable that equals one for ICOs where investors are required to sign up to a whitelist using their wallet address to receive access to the ICO sale (Know Your Customer).
$Modified_{ij}$	Dummy variable that equals one if the rating for ICO j was modified by analyst i at any point in time.
$Month_j$	Dummy variable for each month, indicating the month when an ICO was launched.
$Month_{ij}$	Dummy variable for each month, indicating the month when a rating was given.
MVP_j	Dummy variable that equals one for ICOs with a prototype. A prototype can be a version of a new product with sufficient features to satisfy early adopters (minimum viable product) or drafts of codes on Github.com that are open to discussion by other GitHub users.
$Presale_j$	Dummy variable that equals one if an ICO features a token sale event that runs prior to the official ICO campaign.
$OrderRank_{ij}$	The order rank of the rating by analyst i issued for ICO j in a given month.
$PreviousRatings_j$	Average past TotalRating of all analysts that provide a rating for ICO j
$ReceivedTeamRating_{ij}/$ $ReceivedVisionRating_{ij}/$ $ReceivedProductRating_{ij}/$ $ReceivedTotalRating_{ij}$	Level of the rating when ReciprocalRating dummy equals 1, i.e., level of rating that the analyst of ICO j received for her own ICO from any team member of ICO j prior to the rating issuance date.
$ReciprocalRating_{ij}$	Dummy variable that equals one for reciprocal ratings. A rating is reciprocal when the corresponding analyst has been a team member of another ICO project that previously received a rating by one of the team members of this new ICO. Table 2 represents a hypothetical illustration of our variable composition.
$ReciprocalRatingShare_j$	Share of reciprocal analysts that provide a rating for ICO j .
$RetentionRatio_j$	The percentage of token supply that is retained by the ICO members, and not available for sale.
$ReviewComplexity_j$	The complexity of an analyst's review text, measured by the Gunning (1952) Fog index, and averaged together on ICO level.
$ReviewLength_{ij}$	The natural logarithm of the number of total words in an analyst review. For the $ReviewLength_j$, we measure the natural logarithm of the average review text lengths for ICO j .
$ReviewTone_{ij}$	The tone of the analyst review text. Using the Loughran and McDonald (2011) <i>Positive</i> and <i>Negative</i> word-lists, the tone of a text is defined as the difference between the count of positive and negative words divided by the total words.

$ReviewTone_j$	The tone averaged across all analysts' review texts for ICO j .
$ReviewToneDispersion_j$	The stanard deviation of $ReviewTone_{ij}$ within an ICO.
$ReviewUncertainty_j$	The uncertainty of the analysts' review texts, averaged together on ICO level. Using the Loughran and McDonald (2011) <i>Uncertainty</i> word-list, the uncertainty of a text is defined as the count of uncertain words divided by the total words.
$Scam_j$	Dummy variable that equals one for ICO projects that intentionally defraud investors.
$Success_j$	Dummy variable that equals one for ICOs that completed the token sale and collected (at least \$1) funding.
$StarAnalysts_{ij}$	Dummy variable that equals one when ICO j was rated by one of the top 30 analysts i according to a ranking on ICObench.com.
$StarAnalysts_j$	Share of the top 30 analysts that provide a rating for ICO j .
$TeamRating_{ij}/$ $VisionRating_{ij}/$ $ProductRating_{ij}$	Rating score for Team/ Vision/ Product of an ICO, ranging from 1 (lowest) to 5 (highest).
$TotalRating_{ij}$	The sum of Team, Vision and Product Ratings for the respective ICO, ranging from 3 to 15.
$TotalRating_j$	Average rating of ICO j over all analysts.
$WhitePaper_j$	Dummy variable that equals one if an ICO provides a whitepaper.

Table A2: ICO campaign characteristics.

The table presents applied characteristics during an ICO campaign. (1) A whitepaper is a technical report with a description of consensus algorithm and token metrics. (2) ICO team members announce and promote their project on social media, for example, on Facebook. (3) ICO team members create a forum on bitcointalk.org to discuss and promote their project idea. (4) At pre-sale stage, a set amount of tokens is sold to a limited number of investors before the official crowd sale. (5) Know your Customer (KYC) is a user's identity validation for access to the token sale event. Typically investor's wallet address is used to sign to a whitelist. (6) At bounty programs, rewards and advertising tokens are offered to promote the ICO campaign. (7) Minimum viable product (MVP) is a prototype with minimal features that customer test and employ for future upgrades. It also can be drafts of codes on [Github.com](https://github.com) that are open to discussion by other GitHub users. (8) Bonus displays a quantity discount or a discount program for early-bird investors. (9) Initial Exchange Offerings (IEOs) are ICOs that are conducted on a specific crypto-exchange. (10) Skin in the game or retained exposure which is on average at 46% of the total token supply. (11) The time span between the sale start and end of an ICO is on average 1.7 months.

	No.	thereof succeeded in %
Whitepaper	4,753	36.88
Facebook	4,206	38.14
Bitcointalk	3,067	42.68
Pre-sale	2,817	34.40
Whitelist/KYC	2,593	33.90
Bounty	1,486	33.65
MVP/Prototype	1,050	30.57
Bonus	766	25.33
IEO Launchpad	275	42.91
Retention ratio	46	42.85
Duration	1.7	37.08

Table A3: Ratings and ICO success: An alternative success measure.

This table presents linear regression results for Equation 5. The dependent variable is the natural logarithm of the amount raised by an ICO in columns. The controls for which coefficients are not shown for space reasons include dummies for pre-sale, bonus/bounty options, *KYC*, retention ratio, duration, bitcointalk, and facebook. All specifications include month dummies of the ICOs. All variables are defined in Table A1. *t*-statistics are given in parentheses. The underlying standard errors are robust to heteroskedasticity. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Dep. variable:	<i>AmountRaised_j</i>			
	(1)	(2)	(3)	(4)
<i>TotalRating_j</i>	0.325*** (6.11)	0.390*** (4.74)	0.379*** (3.33)	0.250** (2.17)
<i># Analysts_j</i>	0.097*** (5.11)	0.072*** (3.57)	0.108*** (5.03)	0.080*** (3.62)
<i>StarAnalysts_j</i>		-0.371 (-0.45)	-0.040 (-0.04)	-0.272 (-0.25)
<i>ReciprocalRatingShare_j</i>		-0.402 (-0.39)	0.234 (0.21)	-0.314 (-0.28)
<i>PreviousRatings_j</i>		-0.103 (-0.48)	-0.135 (-0.50)	-0.216 (-0.80)
<i>AnalystDispersion_j</i>		-0.017 (-0.12)	-0.023 (-0.13)	-0.155 (-0.89)
<i>Benchy_j</i>	1.858*** (8.53)	2.062*** (7.38)		2.279*** (5.93)
<i>ReviewToneDispersion_j</i>			-1.535 (-0.26)	-2.529 (-0.43)
<i>ReviewTone_j</i>			2.639 (0.48)	2.872 (0.52)
<i>ReviewUncertainty_j</i>			-15.189 (-0.96)	-16.164 (-1.03)
<i>ReviewComplexity_j</i>			0.019 (0.18)	0.021 (0.19)
<i>ReviewLength_j</i>			0.049 (0.12)	-0.049 (-0.12)
<i>MVP_j</i>			-0.560 (-1.09)	-1.276** (-2.43)
<i>IEO_j</i>			2.328*** (2.74)	2.031** (2.39)
Observations	2378	1629	1128	1128
<i>R</i> ²	0.190	0.208	0.223	0.245
Controls	No	No	Yes	Yes
<i>Month_j Dummies</i>	Yes	Yes	Yes	Yes