The Role of Information Production in Private Markets: Evidence from Initial Coin Offerings

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Abstract

The emerging market for initial coin offering (ICO) has attracted a great deal of interest from policy makers and market participants. One way that this market has developed to overcome information asymmetry is the presence of voluntary ICO experts. We examine the motivation for analysts to provide voluntary ratings and reviews for an ICO, the content of the reviews, and the relation between the reviews and the success of an ICO. The average rating for team, vision, and product is 3.42, 3.45, and 3.18, respectively, on a scale of 1-5. In addition to numerical ratings, experts also provide textual reviews. For ICOs with at least one textual review, on average, there are 4.84 experts per ICO. Review typically consist of 70 words, with 24.96% positive and 4.52% negative. There is likely to be coverage by an expert for ICOs with larger teams, teams that meet KYC verification requirements, and if the industry category is platform. Experienced experts and those who receive more "likes" are more likely to continue reviewing ICOs in the future. More experienced experts tend to write longer reviews. Experts seem to become more "honest" about their reviews as they gain experience and confirmation for their reviews. We find positive reviews to be associated with more funds being raised.

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1. Introduction

A joint PWC and Crypto Valley report "highlights the continued growth and popularity of Initial Coin Offerings (ICOs) globally in 2018, with over 537 ICOs conducted in the first five months of this year, raising a combined total of $13.7 billion USD – more than all ICOs which took place before 2018 combined." The enormous growth of this form of capital has raised several concerns by policy makers and others about the possibility of misrepresentation and manipulation in the offering market. Although the media often characterizes ICOs as an alternative to a public offering, they are more akin to an unregulated form of crowdfunding and unlike other private offerings that are restricted to sophisticated investors, the target investors are mainly retail. This creates the potential for severe information asymmetry and possibly fraud, between the issuing firm and investors.

One way that this market has developed to overcome this information asymmetry is the presence of ICO experts. These experts are akin to analysts in the equity and debt markets to the extent that they provide both a quantitative and qualitative assessment of the ICO's potential. These experts in the ICO market are voluntary, and in many aspects they can also be compared to online experts in other markets where individuals use online platforms to share information about products with the wider community. These reviews have profound implications for businesses.

Although there is a fast-growing academic literature on ICOs, very little is known about the motivation for the voluntary reviews and the content and the effect of the reviews.[1] Our paper aims to fill this void by examining the granular history of the ICO experts' activities on a popular

[1] We provide a detailed literature review in section 2.

ICO listing and rating platform, ICObench. We construct novel measures to answer two sets of research questions (1) What factors motivate the ICO experts to voluntarily submit reviews and do these factors affect the biases of the experts' opinions on an ICO? (2) What is the content of the reviews and does the content reduce information asymmetry for the investors and therefore affect the success of an ICO?

We examine 4345 ICOs during the period 2015 to 2018 on ICObench. A notable feature of the rating system is that if an expert decides to review an ICO, he or she is required to provide a numerical rating but has an option to leave a textual review which can receive "likes" from any user registered on ICObench. The temporal variation in textual review provision and number of likes on the textual reviews for the same expert provides an identification on whether previous community feedback, an external factor, motivates the continuation of textual review provision. We also consider an internal factor, the experience of an expert gained on the rating platform, and analyze whether expert experience motivates the review provision and affects the quality of the reviews.

Our sample of experts cover 2296 ICOs and have provided at least one textual review for 1756 ICOs. We find there is likely to be coverage by an expert for ICOs with larger teams, teams that meet KYC requirements, and if the industry category is platform. These ICO characteristics could be correlated with some expert specific omitted variables that we cannot measure directly such as the expert network or prior expertise. Therefore, in our analysis of motivating factors associated with the rating platform, we control for the expert fixed effects, and we find that more experience and more positive review feedback is associated with a higher likelihood of a subsequent textual review provision. The effect is non-trivial. For example, one standard deviation increase in the experience (or positive review feedback) is associated with 10% (or 7%) higher probability of a textual review provision in the expert's next ICO review. We use the number of days since an ICO expert's first review as a proxy for the experience gained on ICObench. Alternatively, we use the number of ICOs that the expert has reviewed to date as a proxy for experience and find similar results. Our proxy for the community feedback is the average number of likes that the expert received on the previous day that he or she reviewed on ICObench.

Next we focus on understanding the effect of experience and community feedback on the content and the quality of the expert reviews. Our sample of experts write 8493 textual reviews in total. For ICOs with at least one textual review, on average, there are 4.84 experts per ICO. Since the textual reviews are on a social rating platform, the language used is more similar to the one in social media than standard financial disclosure. We apply the Valence Aware Dictionary and Sentiment Reasoner (VADER) to the textual reviews to generate the positive and negative polarity scores.[2] The reviews in our sample on average consist of 70 words per review, with 24.96% positive and 4.52% negative. We find that as the ICO experts gain experience on the rating platform, they tend to write longer reviews. In addition, we find greater experience and more previous positive feedback is associated with fewer positive words on the next textual review, with experience having a stronger effect. For example, one standard deviation increase in the experience (or positive review feedback) is associated with 3% (or 0.6%) less positive words in the next review.

We carry out similar analysis on the numerical ratings provided by the experts. Numerical ratings are provided on a scale of 1-5 across three categories (team, vision, and product). The average rating for team, vision, and product is 3.42, 3.45, and 3.18, respectively. These ratings suggest that experts do not tend to give only high ratings in general. Controlling for the expert

[2] VADER combines sentiment lexicon attuned to microblog-like contexts with rules that embody grammatical and syntactical conventions that humans use when expressing or emphasizing sentiment intensity in social media.

fixed effects, we find that the positive review feedback has a strong effect in reducing the next rating that the expert provides. For example, one standard deviation increase in the positive review feedback is associated with 0.038, 0.047, and 0.056 reduction in rating for team, vision, and product respectively. Experience has a similar but statistically insignificant effect. These findings suggest that experts become more "honest" about their reviews as they gain experience and confirmation for their reviews. These results are consistent with an economic channel that both experience and positive feedback generate a reputation effect that incentivizes the continuation of voluntary review provision. More importantly, such reputation effect improves the quality and reduce the biases in the experts' opinions (Shapiro (1983)).

Although the previous findings are on the positive side, we also document a negative effect on the rating platform. Many ICO review experts also serve as consultants or team members on other ICOs hence creating potential conflicts of interest concerns. We find an association with other similar ICOs makes the experts more, not less, favorable to the ICO they are reviewing in the form of more positive (and less negative) textual reviews and higher numerical ratings.

Our analysis so far focuses on the factors that affect the provision and quality of ICO reviews, we have yet to understand whether such reviews have any real impact on ICO outcomes. The role of experts can be particularly important in this market that has little regulatory oversight. Experts rely on several sources of information, including white papers published by the issuer.[3] It may be difficult for the average investor, however, to assess the validity of the offering from the white paper and to understand the ICO's potential for success. Experts can play a role in helping analyze the content of white papers, in addition to using other sources of information. Therefore,

[3] Most ICOs produce white papers that describe the problem the ICO is to solve, the type of product it will produce, the management team, the number of tokens to be sold, the amount of funds to be raised, and the use of funds. The concept of a white paper is similar to that of an offering prospectus in a traditional capital raising.

the second part of our analysis focuses on understanding the content of the textual reviews and whether such textual content provides information regarding the ICO quality and therefore affects the ICO funding outcome, beyond the effect of numerical ratings and other quantitative ICO characteristics documented in the literature (e.g., Bourveau, De George, Ellahie, and Macciocchi (2018); Lee, Li, and Shin (2018)).

We employ textual analysis to create two sets of textual content measures on the reviews. The first set measures the net sentiment (positive minus negative) of the textual reviews on 3 topics identified by the Latent Dirichlet Allocation (LDA) topic analysis. The second set measures the divergence of opinion in the textual reviews using cosine similarity analysis. Our results suggest that more positive sentiment regarding an ICO in general, or Team, Vision, and Product in particular, is significantly related to more funds raised for the ICO, even after controlling for both the expert numerical rating and the ICObench algorithmic rating. For example, one standard deviation increase in the average sentiment in Team, Vision, and Product is associated with 13%, 15%, and 16% more funds raised in the cross-section of the ICOs. These effects are comparable to the effects of the expert numerical ratings where one standard deviation increase in Team, Vision, and Product is associated with 25%, 26%, and 25% more funds raised respectively. We also find that more convergence of opinions in the textual reviews corresponds to more funds raised. A one standard deviation increase in the convergence of opinions in the textual reviews is associated with 25% more funds raised in the cross-section of ICOs. Overall, these findings suggest that the information produced by the ICO experts is indeed very important to the investors and significantly affects the funding outcome.

2. Literature Review

Our research contributes to two strands of literature. The first area relates to the finance literature that has examined different aspects of ICOs and capital raising. The second area relates to the growing literature on online reviews in the retailing sector. Most ICO capital raising is targeted to retail investors.

Several studies have started to examine the use of ICOs as an alternative to venture capital, crowdfunding, and even IPOs as a mechanism for raising capital. There are theoretical papers that model the offering mechanism and shed light on the role of ICOs in raising capital (see, Canidio (2018), Catalini and Gans (2018), Chod and Lyandres (2018), Cong, Li, and Wang (2018), Li and Mann (2018), and Sockin and Xiong (2018)). The success or failure of ICOs at the time of an offering, and post-ICO performance has also been the subject of research. Success is typically measured by the amount of funds raised and/or whether funding caps have been met at the time of an offering, and post-ICO performance has been proxied by aftermarket returns and liquidity in studies including, Adhami, Giudici, and Matinazzi (2018), Amsden and Schweizer (2018), Benedetti and Kostovetsky (2018), Bourveau, De George, Ellahie, and Macciocchi (2018), De Jong, Roosenboom, and van der Kolk (2018), Dittmar and Wu (2018), Fisch (2018), Howell, Neissner, and Yermack, Hu, Parlour, and Rajan (2018), Huang, Meoli, and Vismara (2018), Lyandres, Palazzo, and Rabetti (2018), Momtaz (2018), Lee, Li, and Shin (2018).

Our analysis complements Bourveau, De George, Ellahie, and Macciocchi (2018), and Lee, Li, and Shin (2018) who find positive analyst ratings in ICOs to be related to the success of an ICO and also the long-run performance in the aftermarket. For example, Lee, Li, and Shin (2018) suggest that the role of analysts in the ICO market could substitute for the role of due diligence done by underwriters in IPOs. A major difference between analysts in the ICO market and underwriters in the IPO market is that these analysts provide ratings voluntarily and are not hired by the issuer. They tend to be individuals unlike underwriter analysts who are part of an investment bank. Our focus is on addressing what factors motivate these voluntary analysts to provide reviews that reflect their genuine belief, if and how they get feedback on their reviews, and the impact of this feedback. In addition to ratings that are used in Bourveau, De George, Ellahie, and Macciocchi (2018) and Lee, Li, and Shin (2018), we conduct a comprehensive analysis of the text of the reviews in order to examine whether the content of the reviews have information over and beyond ratings alone.

Many of the findings in the ICO literature on funding success are similar to those in the crowdfunding literature. Network effects (Mollick, 2014), information on the founding team (Bernstein, Korteweg, and Laws, 2014), soft information (Ivanov and Knyazeva, 2017), and entrepreneurial reputation (Li and Martin, 2016). The role of third party information on success has mixed evidence. Ivanov and Knyazeva (2017) find that platforms and accountants are able to certify issuer quality particularly when information asymmetry is high. Although reviews are generally rare in the crowdfunding space, the two papers we could identify in this space differ in their findings. Using a field experiment in which they provided different degrees of information about intermediaries in crowdfunding, Catalini and Hui (2018) seek to understand what factors drives investors to click on the intermediary’s profile. One type of information provided was a reference: “short reference about the intermediary written by someone in the field (e.g. an entrepreneur that received investment from them).” Despite the importance of reviews in online markets, they do not find that these reviews are effective in increasing click rates. On the other hand, Hornuf and Schwienbacher (2018) document that the number of comments posted on the portal website by crowd investors is positively associated with the number of investments in a given day. However, the economic effect is small due to the fact that most of the comments were in the form of encouragement rather than specific knowledge of the investment.

3. Data and Methodology

3.1 ICO Sample

We obtain data on 4345 ICOs from ICObench.com covering the years 2015 to 2018. As indicated on their website:

> "ICObench is an ICO rating platform supported by investors and financial experts."[4]

ICObench stores the ICO data in dictionary form and provides an Application Programming Interface (API) to retrieve these data. Other studies that have used ICObench data include Howell, Niessner, and Yermack (2018) and Benedetti and Kostovetsky (2018).

Table 1 presents summary information on the sample of ICOs. There is wide variation in the amount of funds raised. On average, an ICO raises $17.1 million. The median is smaller at $5.02 million.[5] The largest ICO by amount of funds raised is Block.one's EOS at $4.2 billion but there is a significant drop off. For example, funds raised by the fifth largest ICO, Huobi, is much lower at $300 million. In total, there are 18 ICOs in our sample that raise $100 million dollars or more. The two largest ICOs cause the mean and standard deviation to be high. It should be noted that proceeds for many ICOs are not reported, this might partly be because they are not completed. Thus, in a few of our tests, we restrict the analysis to only those offerings that report proceeds raised.

As will be shown in later tests, the ICO team is an important component in predicting the outcome of the offering. On average, an ICO has 13 team members with a median of 12. The team

[4] See https://icobench.com/

[5] There are 1296 ICOs with non-missing values for funds raised.

can include people in advisory roles. Given the importance of the team in the amount of proceeds raised, it is not surprising that there have been allegations of some ICOs inflating the number of team members or misrepresenting the composition of the team.

In order to combat fake or misleading information, “Know Your Customer” or KYC process has become popular with ICOs. There are two types of KYCs, one applies to the management team and the other to buyers/investors in the ICO.[6] An individual needs to send in a selfie holding a verification document, such as a passport, in their hand. They also need to provide proof of residency, such as a utility bill. There is some controversy about requiring KYC. On the one hand this verification is needed in order to make sure business is being done with legitimate entities, however, others argue that it undermines the principle of anonymity in this market. In order to combat fake or misleading team information, ICObench offers a KYC process for team members. *Number of KYC Successes* refers to the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. For our sample time period, the average number of success is 0.54.[7] In recent years ICObench has started requiring KYC for teams, and hence our numbers are lower than those reported for recent time periods. In 42% of ICOs buyers/investors had done KYC registration.

A whitelist registration is required in 30% of ICOs. Whitelist registration requires buyers to register and complete KYC in advance, therefore only the payment needs to be made when tokens are actually sold. This requirement is sometimes seen as an indicator of a popular ICO with limited coins to offer. Registration also gives the issuer an indication of investor interest.

[6] KYC in ICOs should not be confused with the KYC procedures of financial intermediaries of FinCen.
[7] The caveat of this measure is that ICObench assigns a value of zero to the ICOs that do not go through the KYC procedure. If we condition on the ICOs that go through the KYC procedure, the number of successes is on average 1.88 and the success rate of a KYC check is around 90%.

In terms of blockchain platforms, the majority of ICOs use Ethereum (87%) that has smart contract functionality for conducting transactions. It is an open blockchain platform that allows development of decentralized applications and makes it easy to create new coins.

Many of the ICOs do not raise fiat currency. Instead, the most popular payment method is Bitcoin (39%), followed by the US dollar and Litecoin (13% each). The payment methods or currency are not exclusive, and an ICO might accept multiple payment methods. Most of the ICOs also provide internet links on various forums and social media. Almost all of ICOs have a website link for the ICO itself, and 96% of them provide a link to the white paper. The white paper is the main document that provides information about the product, problem being addressed and solution, technology, team, funding, and the token. In addition to the ICO website, links related to the ICO are provided on several sites including Facebook, Twitter, Telegram, Bitcointalk, and YouTube as shown in Table 1.

[Table 1 about here]

Table 2 presents the distribution of ICOs by industry category and country. We use industry categories assigned by ICObench. An ICO may be assigned to multiple categories. Although many of the categories are traditional industries such as retail, health care, and banking, the many popular categories are those in blockchain, artificial intelligence, and big data. The most common category is “platforms” with 53.5% of the ICOs and the second most common category is “cryptocurrency” with 38.7% of the ICOs.

One challenge in regulating and overseeing ICO issuance is the heterogeneity in terms of geographic distribution. US issuers are the largest at 12% of all ICOs, followed by Singapore (9%), UK (8%), Russia (6%), Estonia (5%), Switzerland (5%), Hong Kong (3%), Australia (2%), Canada (2%), and Germany (2%) are the ten most popular countries.

[Table 2 about here]

4. ICO Ratings

We first collect data on the two types of ratings provided by ICObench itself. Our primary focus is on the role of voluntary experts who provide scores and written commentary on each ICO. However, we want to control for the ratings provided by ICObench before examining the role of experts. The first type of rating by ICObench uses an automated algorithm, referred to as Benchy that evaluates each ICO on 20 different criteria. The algorithm provides a rating on a scale of 1 to 5 for each ICO based on the following characteristics: team, ICO information, product representation, and marketing/social media. The higher the score the better the ranking. Teams that have participated in multiple ICOs are considered more trustworthy. Product representation is based on information contained in white papers and video presentations. The focus is on the availability of information. Marketing/social media monitors these activities to determine outreach and communication with potential investors. Panel A of Table 3 shows the mean and median Benchy rating for the 4345 ICOs in our sample to be 3.07 and 3.00, respectively.

In addition to the ratings algorithm, ICObench assigns an ICO Success Score (ISS) to each team member. An individual's ISS depends on whether they have been associated with other successful ICOs in the past and the more successful the ICOs the team member has participated in the higher the rating. As an example of the ISS rating, on July 26, 2019, Ian Scarffe was listed as having the highest score of 216.2.[8] On his LinkedIn profile, his title is "Blockchain – ICO/STO Advisor/Consultant/Strategist/Investor." As per his profile, he is listed as an advisor to several ICOs. In Panel B of Table 3, we report ISS values for the team of ICOs in our sample. The mean

[8] https://icobench.com/u/ianscarffe

and median ISS scores for the team are 5.66 and 2.65, respectively. The average of the minimum ISS score among the ICO teams is 2.44 and the maximum is 31.23.[9] The highest ISS score for an individual is 259.56. The scores are quite skewed, 11% of the ICOs have a maximum ISS score of zero. We control for both of these ICObench ratings in analyzing the role of experts.

[Table 3 about here]

5. Ratings and Reviews by Experts

Central to our analysis is the role of the many independent experts who voluntarily provide their own ratings and/or textual reviews. To become an expert an individual applies to ICObench. As per ICObench:

> "Any ICObench user with a fully updated profile (full name, photo, set profile URL, title, bio, location, and a LinkedIn link provided) can apply to become an expert. Depending on the presentation and the answers to the questions asked in the application we decide if a user can become an ICObench expert or not."

Some concerns have been raised about experts having conflicts of interest due to the different roles they play as team members and advisors to other ICOs. Experts are not allowed to take payment for their ratings. In order to mitigate concerns about conflict of interest, ICObench states:

> "Being a part of an ICO isn't a limitation for an application. However, the experts are not allowed to rate the ICOs they participate in (it is technically disabled for them). They are also not allowed to badly rate the competitors or other ICOs with intentions to push their ICO forward on the competitors list."[10]

Each expert assigns a rating of 1 (lowest) to 5 (highest) to three characteristics of the ICO: the team, vision, and product. The criteria for the ratings are as follows: the team is considered better if they have participated in other related projects and/or keeps the community informed

[9] The success of an ICO is determined by funds raised, whether the ICO is exchange traded, and return on investment. ICObench provides a detailed breakdown of how ISS score is determined: https://icobench.com/faq#q-6-4.
[10] https://icobench.com/faq#q-5-6

about the project progress. The ranking for vision is based on the objectives of the project. The rating on product considers whether the projects are in working order or just a concept, technology behind the product, strategy and growth options, and commitment to understanding the market. For example, Hung Chih (Jason Hung) is listed among the top 20 experts on ICObench based on the very high ICO Success Score of 98.8 for ICOs that he has been involved with. He has rated 244 ICOs and the average rating he has given is 3.8. The top-10 experts based on ICO ISS scores, rated 102-684 ICOs, and the average rating varied from 1.1 to 4.2 with only two of them having an average rating above 4.[11] In the case of EOS, the largest ICO, eight experts provided ratings. The weighted average ratings were 4.9 for team, 4.7 for vision, and 4.6 for product. Most of the experts provided comments while a few did not.

Table 4 shows the average numerical ratings given by experts on team, vision, and product. There are 2296 ICOs with numerical ratings.[12] The average ratings for team, vision, and product is 3.42, 3.45, and 3.18, respectively. These ratings suggest that experts do not tend to hype their ratings. However, one potential reason for lower ratings could be conflict of interest that motivates experts to give lower ratings to their competitors. We will examine these issues later.

[Table 4 about here]

In addition to ratings, we also consider the content of an expert's opinion as discussed in their written review. These reviews are very different in content, length, and type of language used from professional reports produced by Wall Street analysts. Below are a few examples of positive and negative comments by an individual expert who provides frequent reviews. [13]

[11] https://icobench.com/u/jason-hung

[12] If we further require an ICO having at least one textual review, the number of ICOs reduces to 1756 as shown in Table 5.

[13] MVP is Minimum Viable Product, the product has been successfully used by real users. Alpha refers to an early test version.

“Very strange project in my opinion. First, they are creating what looks like just a general sandbox of a potential applications. Blurry explanations in WP, lack of MVP kind of gives a hint that the founders are unsure about it themselves. Tried to find some articles with more detailed explanation but failed. Previous experience of the team also raises multiple questions regarding their expertise.”

“Facts: 1) More than one advisor of the project have been claimed to be a scammer and have had expert status revoked which to me is a huge red flag by itself. 2) This is not a blockchain project. I fail to see a need for a technology here. 3) Crypto community have seen plenty of cannabis related projects already. We all know how they usually end up.”

“Very impressive team and advisory board. MVP is there, although I would like to see Alpha as well. KYC passed. Clear vision and solid product and market potential.”

“A good team with good experience in travel industry, also great advisor team. The business model is what the travel industry is in need. With good support I think this would be a potential project to look out for.”

In order to “read’ over 8,000 reviews, we make use of textual analysis both on the sentiment and the content of the reviews. Because the reviews do not correspond to typical financial disclosure but are more similar to customer reviews on retail products, we do not use Loughran and McDonald (2011) financial term dictionary to classify positive and negative discussions. Instead, we classify the sentiment of the review using VADER (Valence Aware Dictionary and Sentiment Reasoner). According to the authors Hutto and Gilbert (2013)

> “VADER uses a combination of qualitative and quantitative methods to produce, and then empirically validate, a gold-standard sentiment lexicon that is especially attuned to microblog-like contexts. We next combine these lexical features with consideration for five generalizable rules that embody grammatical and syntactical conventions that humans use when expressing or emphasizing sentiment intensity. We find that incorporating these heuristics improves the accuracy of the sentiment analysis engine across several domain contexts (social media text, NY Times editorials, movie reviews, and product reviews).VADER has been found to be quite successful when dealing with social media texts, NY Times editorials, movie reviews, and product reviews.”

Thus, the VADER lexicon is well-suited to the task of identifying content of ICO reviews and has the added benefit that it tells us about how positive or negative a sentiment is.

In Panel A of Table 5, we consolidate all the textual reviews at the ICO-level. On average, for the 1,756 ICOs in our sample with at least one textual review, there are 4.84 experts per ICO with a median of two experts. The highest number of textual reviews for an ICO in our sample is 75 for the Sharpay ICO.[14] On average, the number of words in a review of an ICO is 340.73 with a median of 134. The percentage of positive words is 19.27% and negative words is 5.59%. Reviews on average have more positive words than negative.

Panel B of Table 5 provides summary statistics at the review-level based on 8,493 textual reviews contributed by 400 experts. On average a review consists of 70 words, with 24.96% being positive and 4.52% negative. In addition, the textual reviews can receive an “Agree” by other people as is the case with comments on social media. All users registered on ICObench can agree with the review and click the “Agree” button. We refer to these as likes. On average, each review receives 2.44 likes with a median being 1.

In Panel C of Table 5, we further break down the sample by the number of textual experts. The largest number of ICOs (655) have only one textual review. The number of ICOs with 2 or 3 textual reviews is 433, and with 4 to 10 textual reviews is 467. There are 231 ICOs with more than 10 reviews. Interestingly, the amount of funds raised does not necessarily correspond with the number of experts. In fact, the lowest proceeds raised are for ICOs with the most experts. Interestingly, the largest percentage of positive words and the lowest percentage of negative words in the review are for ICOs with only expert. This may be an indication of an affiliated expert trying to increase interest in the ICO.

[Table 5 about here]

[14] Sharpay aims to provide a multi-share button to share content in several social networks in one click. The users receive blockchain-based rewards for sharing or visits of other users via the shared links. This ICO ended on May 31st 2018 and raised $5,973,900. ICObench classifies Sharpay in four categories: business services, communication, cryptocurrency, and media.

6. Motivation for Experts and the Feedback Mechanism

We start this section by addressing the question of which ICOs are likely to be covered by experts. We first examine the determinants of having ICO coverage. To do so, we create an indicator variable, *Expert Coverage*, equal to one if the ICO receives at least one numerical rating, and zero otherwise. We include a number of control variables related to the ICO such as the number of team members and their experience (proxied by the minimum ISS score among the team members), whether the ICO is KYC and whitelist compliant, the number of team members successfully passing the KYC procedure, the number of restricted countries where the ICO cannot be sold, the technical platform of the ICO, the different methods of payment accepted, the availability of various online links (including the white paper availability), industry/category of the ICO, and location.

The results are presented in Table 6. In Column (1) for the full sample of ICOs we find that ICOs with more team members, higher minimum ISS score of team members, success with KYC, with links on certain social media platforms such as YouTube and Bitcointalk, and payment in Waves are more likely to have coverage by experts. The coefficients for these variables are significant at the 1% level. As discussed earlier, there is controversy about KYC registration in an environment that values anonymity. ICOs in the business services, entertainment, and platform industries as well as ICOs from the UK are also more likely to have a numerical rating.

In addition to providing a numerical rating, experts can also take the time to provide written reviews/comments on an ICO. We examine whether characteristics of the ICO are related to the number of experts who have written a textual review for an ICO, the *Number of Experts*. In Column (2), we restrict the sample to only those ICOs that have at least one textual review. We find that there are more likely to be textual reviews for ICOs with larger teams, those that require advance whitelist registration, more KYC successes, a link on Bitcointalk, and if the ICO industry category is platform. In columns (3) and (4), we include the Benchy rating for the ICO that is based on an algorithm. Higher Benchy ratings are associated with more expert coverage. Even after controlling for Benchy ratings, the attributes mentioned above continue to be significant in explaining expert coverage.

[Table 6 about here]

We next examine whether the probability of providing a subsequent review is due to the expert's experience and/or the number of likes s/he receives on a prior review. In the analysis presented in Table 7, the dependent variable is equal to one if the expert reviews the next ICO, zero otherwise. We also include expert fixed effects in models (2)-(4). We proxy for the experience of the expert by either the number of days since his/her first ICO review or by the number of ICOs reviewed. The results using either variable are similar and we only report results for number of days since first review. In Panel A, we show that the probability of reviewing the next ICO is positively related to the number of days since the expert's first review. Therefore, the longer the expert has been active, the more likely that they will continue to do reviews. We next examine the effect of feedback from the community. In Panel B, we show that the experts are more likely to continue doing reviews if they receive likes from the community. The feedback from the community motivates them to continue doing reviews. There is no button for "Disagree" therefore we cannot study if there is any negative impact.

In Panel C, we combine expert experience and the number of likes to see what may lead an expert to review again. In all specifications, we find that both the number of likes and expert experience are significant and positive. Collectively, these results suggest that the probability of providing a review on the next ICO is increasing in the experience of the expert and whether they receive positive feedback. Therefore, both experience and acceptance of reviews by the community are important motivators.

[Table 7 about here]

Next, we examine whether the number of likes and the expert's past experience has a relation to the tone of their review in the next ICO. The dependent variables are the number of words used and the proportion of words in the expert that are positive or negative. These variables are averaged over the day if an analyst provides textual reviews to multiple ICOs. As shown in Panel A of Table 8A, more experienced experts, measured as the log of number of days since the first review, tend to provide reviews in the future that are longer. Experience is positively related to average number of words. Furthermore, the greater the experience, the lower are the percentage of positive words used in subsequent reviews. We also examine the impact of likes from previous reviews on future reviews. The number of likes is associated with fewer positive words as shown in Panel B of Table 8A. However, the coefficient of likes is only significant at the 10% level. Finally, we examine the combined impact of experience and community feedback on future reviews. Experience continues to be significant but number of likes is not significant.

[Table 8A about here]

We carry out similar analysis on the numerical ratings provided by the experts. The results are reported in Table 8B. We find that the positive review feedback has a strong effect in reducing the next rating that the expert provides. The results are stronger in rating for product and vision. Experience has a similar but statistically insignificant effect. The findings from Table 8A and Table 8B suggest that experts become more "honest" about their reviews as they gain experience and confirmation for their reviews. These results are consistent with an economic channel that both experience and positive feedback generate a reputation effect that incentivizes the continuation of voluntary review provision. More importantly, such reputation effect improves the quality and reduce the biases in the experts' opinions (Shapiro (1983)).

[Table 8B about here]

We next examine whether an expert's past history as a team member in a particular industry category predicts the tone of his next review. There are two potential relationships between the expert experience in a particular industry and the tonal content. First, if the expert was involved as a team member in a prior ICO in the same category, he may be more negative about the ICO in order to make his ICO look better. On the other hand, perhaps experts collude to rate each other's ICOs higher in order to increase the amount of proceeds. Or, they simply provide their honest opinion.

In order to test this hypothesis, we create a variable, *Expert Common Category*, which is the number of common industries or categories for which the expert was a team member prior to the review. As an example, assume John is an expert providing review for ICO A. We search the ICO database to determine any other ICOs for which John is involved as a team member. Let's say John is involved in ICO B, C, and D. We compare the categories of B, C, D and see how many of these are the same as the categories of A (each ICO could have multiple categories). *Expert Common Category* captures the number of common categories.

Table 9 presents the results of the effect of the expert's prior association as a team member with ICOs in the same category. The dependent variable is the percentage of words that are positive or negative, as well as the numerical ratings on the team, product, and vision. We include two different specifications, Panel A of Table 9 reports results with expert fixed effects, and Panel B with ICO fixed effects.

We find that experts who are involved as a team member in more ICOs in the same category as the rated ICO are likely to have more positive words and less negative words in their textual review content and to rate the qualities of the ICO higher on team, product and vision in the numerical ratings. In the specifications of expert fixed effects, it is notable that the team, product and vision are all rated as higher if the expert was a team member in the same category as the current ICO. When using ICO fixed effects, product and vision continue to be significant. Overall, the results of this table indicate that experts' past association with an ICO category makes them more favorable to the current ICO both in numerical ratings and the textual reviews. In particular, the results controlling for the expert fixed effects suggest the findings are not driven by their expertise in a common category, but instead more likely driven by colluding incentives.

[Table 9 about here]

7. Ratings, Content of Reviews, and the Success of an ICO

Finally, we examine the relationship between the content of reviews and the success of an ICO as measured by the amount of funds raised in U.S. dollars. To understand the actual content of the textual reviews, we perform topic analysis using Latent Dirichelet Allocation (LDA) on all the textual reviews. LDA is a dimensionality reduction algorithm used extensively in computational linguistics (Blei, Ng, and Jordan 2003). LDA assumes an underlying model in which each topic in a review is generated from a probability distribution over topics. Potential topics might include the experience of the team, the use of blockchain, and a description of the product. Each of these different topics will have a vocabulary related to the discussion and through probabilistic modelling, LDA discovers the different topics that the corpus of all reviews contain.

One benefit of LDA is that it requires only one input from the user: the number of topics to be generated. Because the reviews are generally short and contain few individual topics, we set the number of topics to five.[15] LDA produces both topic loading for each ICO with a review of each of the five topics discussed by the experts and a set of words and their frequencies for each topic. In Table 10 and Figure 1, we show the top 10 terms of each of the five individual topics. A manual inspection of the topics suggest that Topic 1 is related to discussions around the ICO or security, Topic 2 is about the platform or blockchain used for the token focusing on the technical aspect of ICOs, Topic 3 is a discussion of the product and vision focusing on the idea underlying the ICOs, Topic 4 is about the team focusing on the management and advisor experience, and Topic 5 is about available information on the ICOs. In general, the content of the topic analysis corresponds to the three individual categories of the expert's numerical ratings pre-specified by ICObench.

[Figure 1 and Table 10 about here]

In order to categorize the average sentiment of each review, we use the top key words of the LDA to classify each sentence of all reviews into three categories shown in Table 11. The key words are team, vision, and product. These keywords are chosen to mirror the types of attributes that comprise the numerical rating of the expert. We analyze the effect of sentiment on proceeds raised after controlling for other aspects of the ICO such as the numerical rating on the attributes, the number of team members, the minimum ISS (ICO success score) of the team members, whether the ICO requires KYC or Whitelist for its investors, the number of ICO team members successfully passing ICObench KYC requirement (Number of KYC successes), and the number of restricted countries where the ICO cannot be sold. Furthermore, we control for a number of fixed effects:

[15] We manually determine that five is the most reasonable number. There is too much overlap among topics if the number is increased.

the type of platform, the industry or category of the ICO, the type of currency accepted, and the country of origin.

In all specifications of Table 11, the higher the numerical rating by experts on the team, vision, and product, the greater the funds raised. Funds raised are also higher if there are more team members but smaller when there are a larger number of KYC successes.[16] We do not find any statistically significant relationship between proceeds raised and whether the offering requires KYC compliant or there are a larger number of countries where the ICO is restricted from selling.

Examining the effect of sentiment, we show that the greater the sentiment (more positive) on all aspects of the ICO such as the team, product and blockchain, the higher the proceeds raised even after controlling for the quantitative ratings and other ICO characteristics. This suggests that the textual review content contains valuable information relating to the real outcomes of the ICOs.

[Table 11 about here]

Next, we examine whether divergence of opinion affects the proceeds raised. We use the average cosine similarity of all reviews in an ICO. The cosine similarity for each review is a normalized pairwise comparison of the review with all other reviews. To calculate the cosine similarity we create a vector of words used throughout the entire review corpus and populate the vector with the number of times the word appears in a review. Because the corpus contains many words, many of the elements in the vector are set to zero. Cosine similarity compares the distance between two vectors. If two experts say almost identical things about an ICO, their cosine

[16] The negative relationship between the funds raised and the number of KYC successes might appear counter intuitive. However, this may be related to the specific requirements of team member KYC by ICObench. The team member KYC requirement by ICObench is voluntary and only becomes mandatory if ICObench finds an ICO suspicious. Therefore, for ICOs that do not go through the team member KYC requirement and ICObench also do not find suspicious, ICObench records the number of KYC successes as 0. We find that the number of KYC successes would appear as 0 for 70% of the ICOs that do not have to go through the team member KYC procedure but the quality of these ICOs might actually be high. As a result, the negative relationship could simply reflect the majority of the ICOs not having to go through the KYC procedure.

similarity will be close to one. If they say completely different things, the cosine similarity will be close to zero. We then average all of the cosine similarities for the experts in an ICO with the expectation that divergence of opinion is greater when cosine similarity is lower. In other words, the more experts disagree about the ICO, the fewer words they will have in common and the lower will be the cosine similarity.

We predict that the lower (greater) the divergence (consensus) of opinion regarding the ICO, the higher (lower) will be the proceeds raised. In Table 12, we control for the numerical ratings and still find that the lower the divergence of opinion (greater consensus) among experts, the higher the proceeds raised. This means that when experts agree proceeds are higher and when they disagree, proceeds are lower. Overall, the findings of this section highlight the importance experts have in determining the amount of proceeds raised.

[Table 12 about here]

8. Conclusions

The growth of ICOs has raised several concerns by policy makers and others around the world about the possibility of misrepresentation and manipulation. One way that this market has developed to overcome information asymmetry is the presence of ICO experts. The role of experts can be particularly important in a financial market that has little regulatory oversight. These experts are voluntary, and in many aspects they can also be compared to online experts in other markets where individuals use online platforms to share information about products with the wider community. Their reviews have profound implications for businesses.

We believe ours is the first paper to examine the role of voluntary experts in the ICO market, and our results have implications for other markets where voluntary reviews exist. The average rating given by experts to an ICO for team, vision, and product is 3.42, 3.45, and 3.18, respectively. These ratings suggest that experts do not hype their ratings. In addition to numerical ratings, experts also provide textual reviews. For ICOs with at least one textual review, on average, there are 4.84 experts per ICO. A review, on average, consists of 70 words, with 24.96% positive and 4.52% negative. Experts are more likely to provide reviews of ICOs that has larger teams, teams that meet KYC requirements, and if the industry category is platform.

Experts who are more experienced and those receive more "likes" from the community are more likely to continue reviewing ICOs in the future. More experienced experts tend to write longer reviews. We find greater experience and more likes by readers is associated with fewer positive words. Experts can themselves be team members/advisors in other ICOs, hence creating a conflict. We find an association with other similar ICOs makes them more, not less, favorable to the ICO they are reviewing. Finally, we show the textual reviews have value over and above numerical ratings provided by experts and platforms such as ICObench. Positive opinions are associated with more funds being raised.

Our paper examines many interesting questions about the role of voluntary reviews in reducing information asymmetry in an unregulated market. Our results should be of interest to policy makers, market participants, buyers of ICOs, and the associated expert community. Our findings also shed light on a new, innovative, and yet little understood mechanism for capital raising in the private markets.

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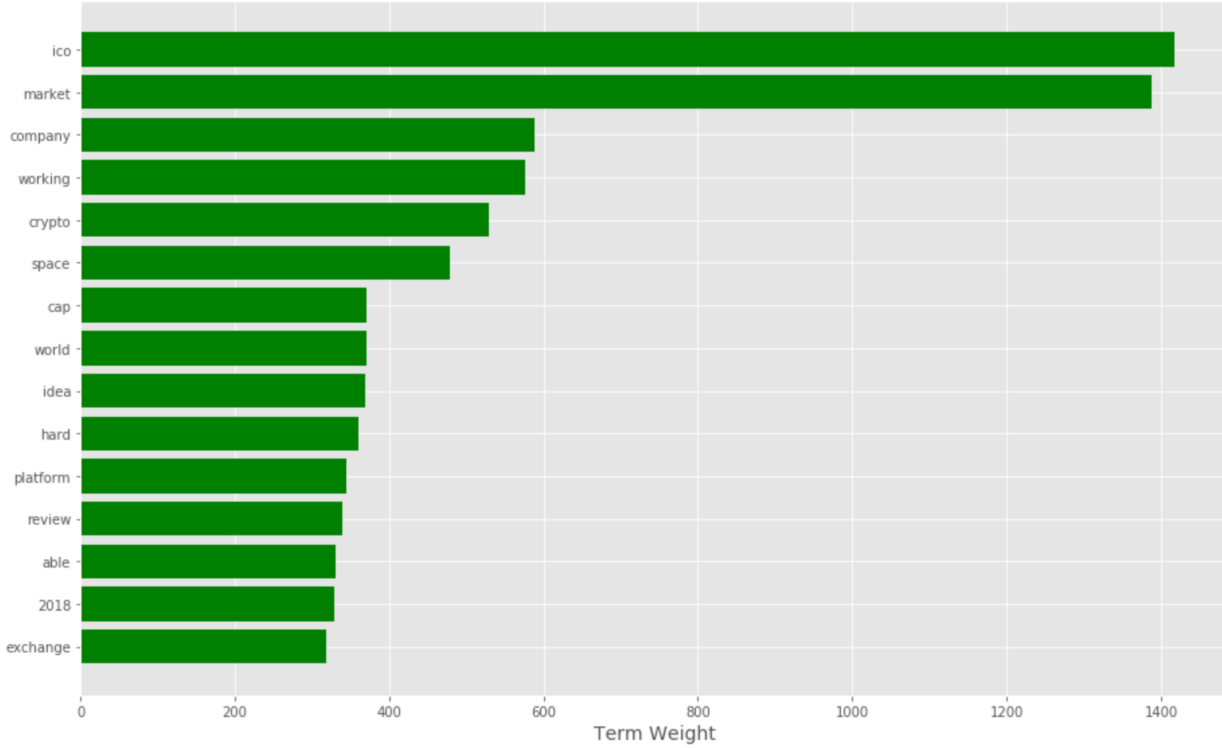
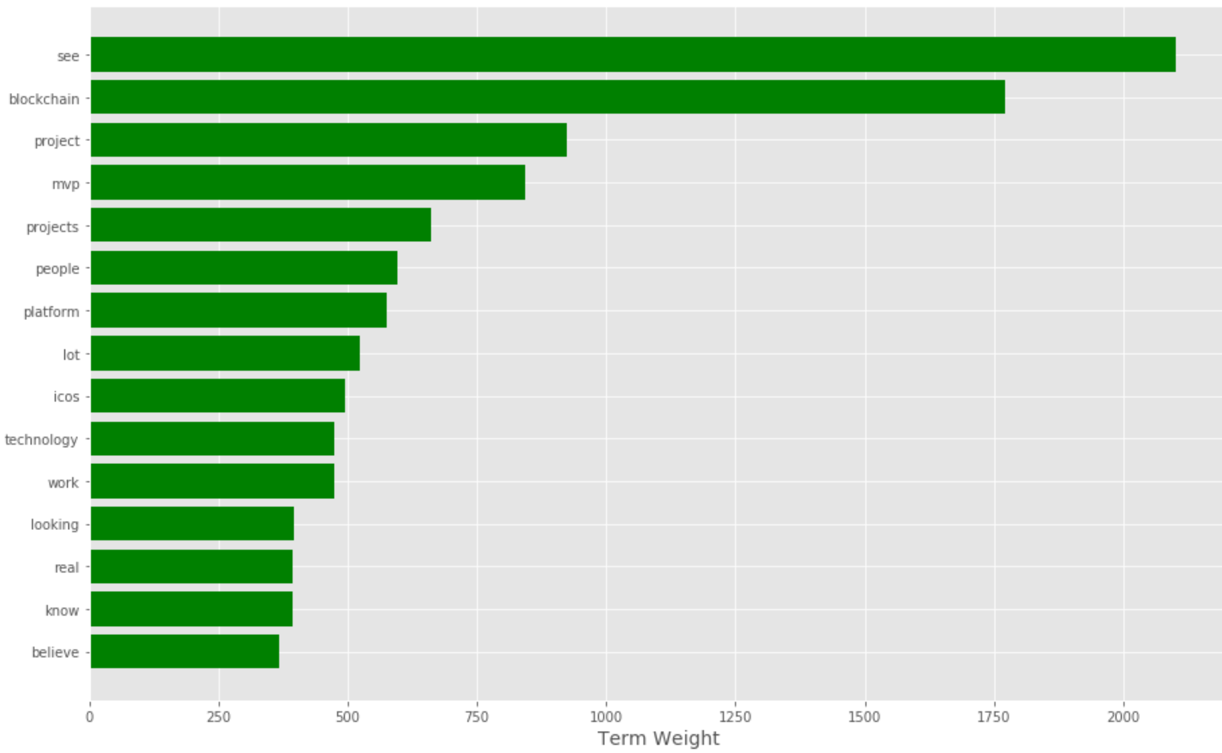
Figure 1
Bar Chart of the Topic Terms for the Top Five Topics

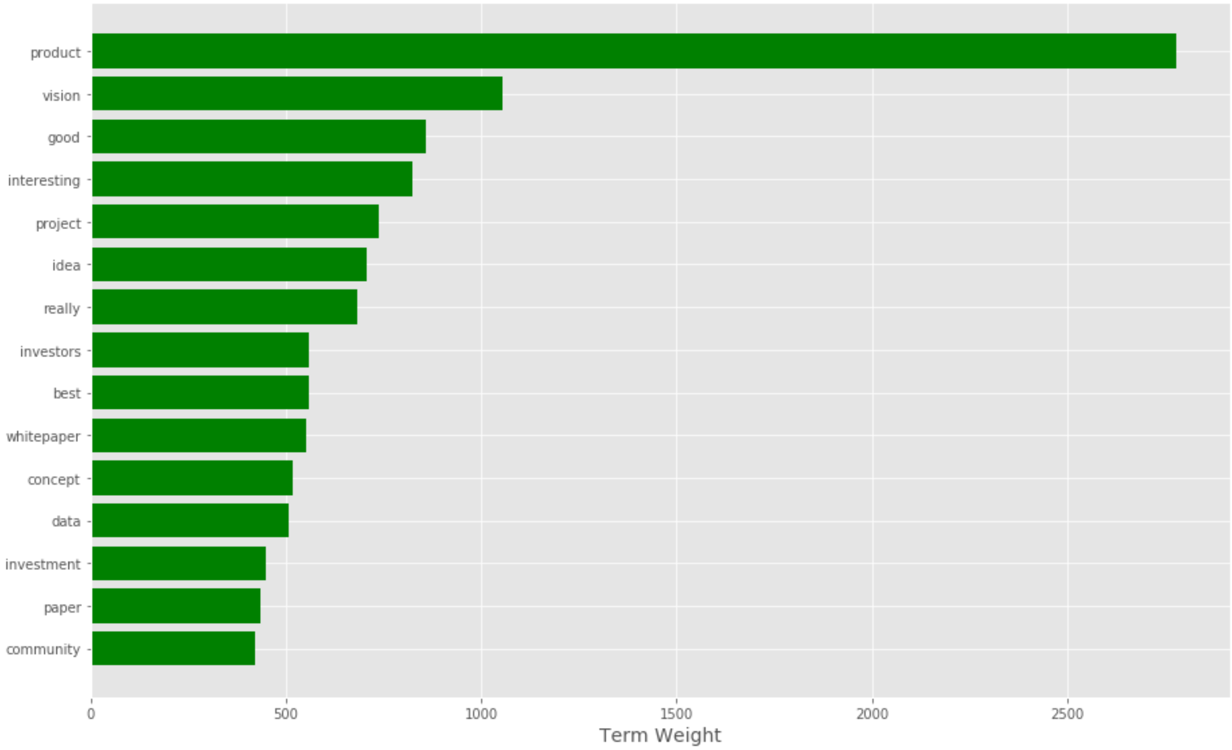
Topic 1:



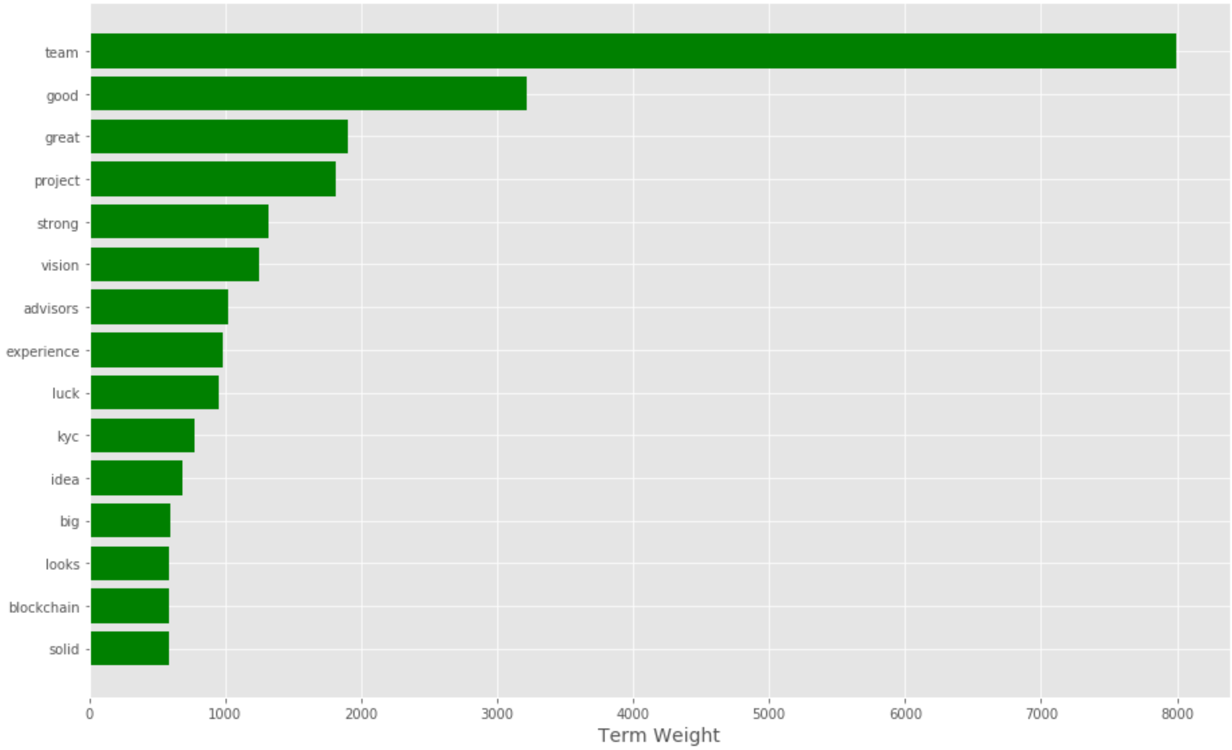
Topic 2:



Topic 3:



Topic 4:



Topic 5:

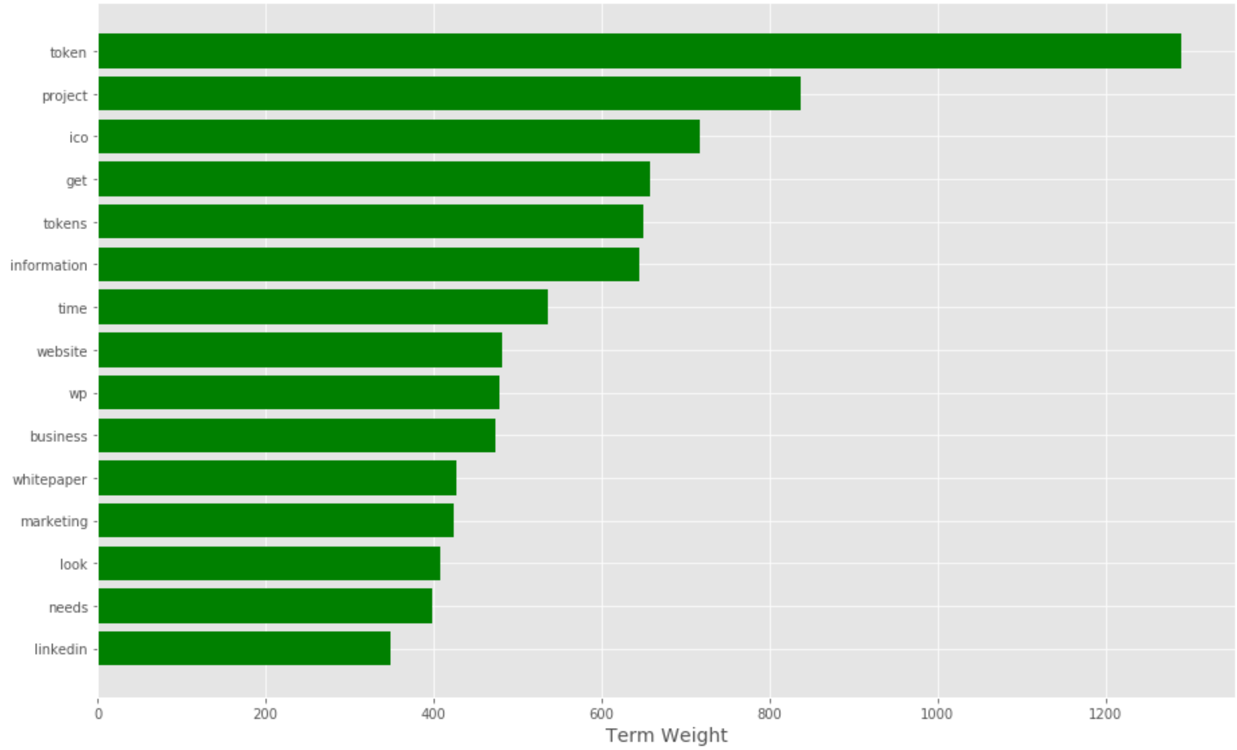

token
project
ico
get
tokens
information
time
website
wp
business
whitepaper
marketing
look
needs
linkedin
0
200
400
600
800
1000
1200
Term Weight

Table 1
ICO Characteristics

The table reports the number of observations (N), mean, median and standard deviation for the characteristics of 4,345 ICOs for the period January, 2015-September, 2018. *Funds Raised* is the amount of funds raised in the offering in million USD, this information is available for 1,296 ICOs. *Soft cap* is the minimum amount of funds to be raised. *Hard cap* is the maximum amount of funds to be raised. *Duration of Offering* is the number of days the offering was open. *Number of Team Members* is the number of team members reported by the ICO issuer. *KYC* or Know Your Customer is a proof of identity used in ICOs. *KYC Registration* equals one if the buyer/investor provides registration information. Number of *KYC Successes* is the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. *Whitelist* is a dummy variable that takes the value of one if investors are required to register for the ICO in advance and provide KYC identity proof. *Number of Restricted Countries* is the number of countries in which the ICO cannot be sold. *Platform Used* shows the proportion of ICOs using Ethereum, Waves or Utility Token, the three most popular platforms. *Currency of Payment Accepted* shows the proportion of ICOs accepting the US dollar, Bitcoin, Litecoin, and Waves token. *Whitepaper Link* is the proportion of ICOs for which one or more link is provided for the ICO's whitepaper. The link can be provided on multiple sites such as Reddit, Medium, Slack, Facebook, and Youtube as shown below.

	N	Mean	Median	Std Dev
Funds Raised ($ million)	1296	17.1	5.02	128
Soft Cap ($ million)	1666	5.16	2.50	13.53
Hard Cap ($ million)	2296	47.08	20.00	372.33
Duration of Offering (days)	3357	57.46	36.00	64.91
Number of Team Members	4049	13.15	12	7.88
KYC Registration	4345	0.42	0.00	0.49
Whitelist Registration	4345	0.30	0.00	0.46
Number of KYC Successes	4345	0.54	0.00	0.97
Number on Restricted Countries	4345	1.09	0	3.57
Platform Used				
- Ethereum Blockchain	4345	0.87	1	0.34
- Waves Blockchain	4345	0.03	0	0.17
- Utility Token	4345	0.01	0	0.08
Currency of Payment Accepted				
- US Dollar	4345	0.13	0	0.34
- Bitcoin	4345	0.39	0	0.49
- Litecoin	4345	0.13	0	0.34
- Waves Token	4345	0.01	0	0.12
Web Links				
- Whitepaper Link	4345	0.96	1	0.2
- Reddit Link	4345	0.56	1	0.5
- Medium Link	4345	0.66	1	0.47
- Slack Link	4345	0.18	0	0.39

-	Discord Link	4345	0.07	0	0.25
-	Telegram Link	4345	0.81	1	0.39
-	Twitter Link	4345	0.95	1	0.22
-	Youtube Link	4345	0.68	1	0.46
-	ICO Website Link	4345	0.99	1	0.11
-	Github Link	4345	0.51	1	0.5
-	Facebook Link	4345	0.86	1	0.34
-	Bitcointalk Link	4345	0.68	1	0.47
-	Bounty Link	4345	0.33	0	0.47

Table 2
ICOs by Industry and Country

The distribution of ICOs by industry category is presented below in columns 1 and 2. We use the categories as assigned by ICObench. An ICO can be assigned to more than one category. Some categories are traditional industries, while others such as Platform, Cryptocurrency, and Smart Contract are newer categories relevant for ICOs. Columns 3 and 4 report on the country of incorporation.

(1)	(2)	(3)	(4)
Category	**% of ICOs**	**Country**	**% of ICOs**
Platform	54%	USA	12%
Cryptocurrency	39%	Singapore	9%
Business services	23%	UK	8%
Investment	18%	Russia	6%
Software	15%	Estonia	5%
Smart Contract	14%	Switzerland	5%
Internet	12%	HongKong	3%
Entertainment	11%	Australia	2%
Infrastructure	10%	Canada	2%
Banking	10%	Germany	2%
Artificial Intelligence	9%	Netherland	2%
Communication	8%	Cayman Islands	2%
Big Data	8%	Malta	2%
Media	7%	Gibraltar	1%
Other	7%	British Virgin Islands	1%
Retail	6%	France	1%
Health	5%	India	1%
Real estate	4%	Japan	1%
Education	4%	Slovenia	1%
Tourism	3%	UAE	1%

Table 3
Ratings of ICOs by ICObench

Panel A presents the number of observations (N), mean and median for each rating attribute. *Benchy Rating* is a rating assigned to an ICO based on 20 criteria determined by ICObench using an automated algorithm. The rating scale is 1-5. In addition, ICObench assigns an ICO Success Score (ISS) to each team member that is based on the team member's participation in past successful ICOs. *Maximum* and *Minimum ISS Score of Team Members* is the maximum and minimum ISS score assigned to a team member. Panel B shows the mean and median scores assigned by experts.

Panel A: Benchy Ratings			
	N	Mean	Median
Benchy Rating	4345	3.07	3.00

Panel B: ICO Success Scores (ISS)			
	N	Mean	Median
Mean ISS Score of Team Members	4049	5.66	3.40
Median ISS Score of Team Members	4049	2.65	2.60
Maximum ISS Score of Team Members	4049	31.23	7.00
Minimum ISS Score of Team Members	4049	2.44	2.50

Table 4
Numerical Ratings of ICOs by Experts

Experts provide numerical scores and textual reviews for an ICO. For the numerical score, each expert assigns a rating of 1 to 5 on three characteristics: Team, Vision, and Product on a scale of 1-5. The score on *Rating-Team* is based on attributes such as whether the team has participated in other related projects and/or keeps the community informed about the progress of the project. *Rating-Vision* is based on the vision of the project. *Rating-Product* considers whether the project is in working order or concept, technology behind the product, and strategy and growth options.

Expert Ratings			
	N	Mean	Median
Rating-Team	2296	3.42	3.8
Rating-Vision	2296	3.45	3.7
Rating-Product	2296	3.18	3.4

Table 5
Reviews by Experts

Experts provide numerical scores and textual commentary for an ICO. We classify the sentiment of the review using VADER (Valence Aware Dictionary and Sentiment Reasoner) as proposed by Hutto and Gilbert (2013). According to Hutto and Gilbert (2013), VADER uses a combination of qualitative and quantitative methods to produce, and then empirically validate, a sentiment lexicon that is especially attuned to microblog-like contexts. Panel A reports the mean, median, and standard deviation of *Number of Experts*, *Number of Words in Review*, *% Positive Words*, and *% Negative Words* at the ICO-level. Panel B provides the same information at the reviewer-level. We also include *Number of Likes* for the reviewer. In Panel C, the sample is split by groups based on number of experts covering an ICO.

Panel A: ICO-Level Review Information (N=1756)

	Mean	Median	Std Dev
Number of Experts	4.84	2.00	6.64
Number of Words in Review	340.73	134.00	542.83
% Positive Words	19.27	17.65	12.31
% Negative Words	5.59	4.00	6.35

Panel B: Review-Level Information (N=8493)

	Mean	Median	Std Dev
Number of Words in Review	70.45	44.00	119.77
% Positive Words	24.96	20.60	19.16
% Negative Words	4.52	0.00	7.79
Number of Likes	2.44	1.00	4.81

Panel C: ICO-Level Review Information by Number of Experts Covering ICO

	All	1	2-3	4-10	>10
Number of ICOs	1756	655	433	467	231
Median Funds Raised ($ mill)	5.02	7.01	7.25	8.11	6.11
Number of words in reviews	340.73	75.74	176.42	421.73	1286.05
% Positive words	19.27	19.98	18.54	18.89	19.35
% Negative words	5.59	6.23	6.03	4.87	4.21

Table 6
Determinants of Expert Coverage

This table shows the relation between expert coverage and ICO attributes. The dependent variable is *Expert Coverage* takes the value of one if an expert provides a numerical ranking to an ICO, otherwise it is zero. The second dependent variable is *Log of the Number of Experts* that provide a textual review of an ICO. *Number of Team Members* is the number of team members reported by the ICO issuer. ICObench assigns an ICO Success Score (ISS) to each team member that is based on the team member's participation in past successful ICOs, *Minimum ISS Score of Team* is the minimum ISS score assigned to a team member. *KYC* or Know Your Customer is a proof of identity used in ICOs. *KYC Registration* equals one if the buyer/investor provides registration information. *Number of KYC Successes* is the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. *Whitelist* is a dummy variable that takes the value of one if investors are required to register for the ICO in advance and provide KYC identity proof. *Benchy Rating* is a rating assigned on a scale of 1-5 to an ICO based on 20 criteria determined by ICObench using an automated algorithm. *Number of Restricted Countries* is the number of countries in which the ICO cannot be sold. We include dummies for venues for Whitepaper Link, industry, currency of payment accepted, and country from which the ICO is issued.

	(1)	(2)	(3)	(4)
	Expert Coverage	*Log of the Number of Experts*	Expert Coverage	*Log of the Number of Experts*
Number of Team Members	0.036***	0.021***	0.032***	0.017***
	(6.59)	(7.22)	(5.77)	(5.84)
Minimum ISS Score of Team Members	0.047***	0.004	0.029	-0.021*
	(2.75)	(0.39)	(1.60)	(-1.96)
KYC Registration	-0.407***	-0.077	-0.440***	-0.120**
	(-4.26)	(-1.37)	(-4.61)	(-2.16)
Whitelist Registration	-0.021	0.111**	-0.029	0.091*
	(-0.23)	(2.05)	(-0.31)	(1.73)
Number of KYC Successes	0.609***	0.298***	0.523***	0.200***
	(11.78)	(11.79)	(8.52)	(7.08)
Benchy Rating			0.261***	0.319***
			(3.04)	(6.66)
Number of Restricted Countries	0.007	-0.003	0.006	-0.004
	(0.71)	(-0.76)	(0.57)	(-0.99)
Twitter Link	0.002	-0.149	-0.061	-0.179
	(0.01)	(-1.23)	(-0.32)	(-1.41)
Facebook Link	-0.001	0.032	-0.102	-0.115
	(-0.01)	(0.48)	(-0.82)	(-1.58)
Telegram Link	-0.129	0.091	-0.178*	-0.005
	(-1.25)	(1.42)	(-1.71)	(-0.07)
Youtube Link	0.476***	0.137**	0.420***	0.042
	(5.78)	(2.47)	(5.00)	(0.74)
Bitcointalk Link	0.710***	0.230***	0.622***	0.089

	(8.60)	(4.06)	(7.19)	(1.47)
Banking	0.163	-0.107	0.168	-0.086
	(1.38)	(-1.49)	(1.41)	(-1.20)
Business services	0.181**	0.126**	0.169**	0.114**
	(2.12)	(2.44)	(1.98)	(2.25)
Media	-0.086	0.216**	-0.101	0.214**
	(-0.59)	(2.34)	(-0.69)	(2.36)
Entertainment	0.237**	0.054	0.229**	0.029
	(2.04)	(0.76)	(1.97)	(0.43)
Tourism	0.131	-0.067	0.119	-0.073
	(0.61)	(-0.58)	(0.56)	(-0.67)
Platform	0.176**	0.126***	0.171**	0.128***
	(2.47)	(2.81)	(2.40)	(2.89)
Payment Accepted in USD	-0.089	-0.069	-0.093	-0.075
	(-0.80)	(-1.06)	(-0.83)	(-1.19)
Payment Accepted in Bitcoin	0.061	0.077	0.048	0.075
	(0.71)	(1.44)	(0.54)	(1.43)
Payment Accepted in Litecoin	0.085	0.064	0.079	0.058
	(0.72)	(0.96)	(0.66)	(0.88)
Payment Accepted in WAVES	0.617**	-0.105	0.631**	-0.115
	(2.03)	(-1.04)	(2.06)	(-0.95)
British Virgin Island	0.206	0.148	0.193	0.127
	(0.68)	(0.89)	(0.63)	(0.78)
Cayman	0.536**	0.111	0.525**	0.111
	(2.07)	(0.85)	(2.01)	(0.88)
China	-0.095	0.003	-0.109	0.051
	(-0.24)	(0.01)	(-0.28)	(0.17)
Gibraltar	0.763**	0.247	0.737**	0.222
	(2.50)	(1.61)	(2.42)	(1.45)
Italy	0.641	-0.180	0.659	-0.092
	(1.10)	(-0.74)	(1.13)	(-0.36)
Korea	0.696	-0.139	0.662	-0.185
	(1.17)	(-0.45)	(1.10)	(-0.60)
Latvia	-0.270	0.390	-0.276	0.367
	(-0.52)	(1.54)	(-0.54)	(1.40)
Lithuania	1.059**	0.521**	1.041**	0.485**
	(2.24)	(2.50)	(2.17)	(2.29)
Malaysia	-0.537	-0.296	-0.556	-0.255
	(-1.00)	(-0.79)	(-1.03)	(-0.66)
Nigeria	-1.342**	-0.508	-1.343**	-0.500
	(-2.01)	(-1.29)	(-2.04)	(-1.10)
Philippines	-0.417	0.761	-0.407	0.720
	(-0.86)	(1.45)	(-0.85)	(1.25)

Singapore	0.152	0.010	0.130	-0.021
	(1.16)	(0.14)	(0.99)	(-0.30)
Slovenia	0.846**	-0.023	0.826**	-0.003
	(2.24)	(-0.12)	(2.19)	(-0.02)
Switzerland	0.245	0.031	0.243	0.026
	(1.45)	(0.34)	(1.43)	(0.29)
Taiwan	-0.002	-0.188	-0.045	-0.169
	(-0.00)	(-0.47)	(-0.08)	(-0.41)
Thailand	0.049	-0.719*	0.080	-0.737*
	(0.09)	(-1.68)	(0.15)	(-1.75)
Turkey	-0.131	-0.408***	-0.130	-0.493***
	(-0.19)	(-4.22)	(-0.19)	(-5.14)
UK	0.387***	0.015	0.385***	0.018
	(2.95)	(0.20)	(2.93)	(0.23)
USA	0.234**	0.057	0.236**	0.047
	(2.15)	(0.85)	(2.16)	(0.71)
Constant	-1.620***	-0.095	-1.973***	-0.496***
	(-8.06)	(-0.80)	(-8.25)	(-3.54)
Observations	4049	1664	4049	1664
Pseudo/Adjusted R-squared	0.142	0.274	0.144	0.294

Table 7
Factors Impacting the Probability of a Subsequent Textual Review

The table shows the relation between subsequent reviews and prior experience (Panel A) and community Feedback (Panel B), and combined impact of prior experience and community feedback. The dependent variable Subsequent Review takes the value of 1 if the expert provides at least one textual review on day t+1, and 0 if the expert provides a numerical rating but does not provide a textual review. The independent variables *Ln (# of Days Since First ICO Review)* and *Ln (Number of Likes)* are measured using information up to day t. *Ln (# of Days Since First ICO Review)* is defined as the logarithm of the number of days has elapsed since an expert provided the first review on ICObench. *Ln (Number of Likes)* measures the logarithm of 1 plus the number of likes on an expert's textual reviews provided on day t. We do not impose any conditions on the sample used in columns (1) and (2). In column (3), we require that the expert provides at least one textual review on day t. In column (4), we require that the expert's textual review on day t receives at least one like. Column (1) does not include expert fixed effects, columns (2), (3) and (4) includes expert fixed effects. The relation between subsequent reviews and expert experience, proxied by *Ln (# of Days Since First ICO Review)* is reported in Panel A, community feedback proxied by *Ln (Number of Likes)* in Panel B; and the combination of experience and community feedback in Panel C.

	(1)	(2)	(3)	(4)
	Subsequent Review	Subsequent Review	Subsequent Review if the Reviewer has Reviewed Before	Subsequent Review if the Past Review had at least one Like
Panel A: Expert Experience: Number of Days since the First ICO Review				
Ln (# of Days Since First ICO Review)	0.025***	0.052***	0.035***	0.036***
	(4.04)	(5.70)	(5.47)	(4.86)
Expert FE	No	Yes	Yes	Yes
Observations	5945	5945	4657	3667
Adjusted R-squared	0.008	0.341	0.264	0.274
Panel B: Community Feedback: Number of Likes from Previous Review				
Ln (Number of Likes)	0.160***	0.108***	0.025***	0.040***
	(10.06)	(6.20)	(2.78)	(3.19)
Expert FE	No	Yes	Yes	Yes
Observations	5487	5487	4199	3209
Adjusted R-squared	0.083	0.327	0.171	0.173
Panel C: Combined Effect of Experience and Community Feedback				
Ln (# of Days Since the First ICO Review)	0.013*	0.065***	0.027***	0.021*
	(1.77)	(5.69)	(3.02)	(1.92)
Ln (Number of Likes)	0.157***	0.096***	0.024***	0.037***
	(9.97)	(6.41)	(2.73)	(3.11)
Expert FE	No	Yes	Yes	Yes
Observations	5487	5487	4199	3209
Adjusted R-squared	0.084	0.347	0.177	0.176

Table 8A
Impact of Expert Experience and Community Feedback on Textual Review Content

The table shows the relation between the content of expert reviews and prior experience (Panel A) and community Feedback (Panel B), and combined impact of prior experience and community feedback. The content of expert reviews is proxied by 1) *Average Number of Words in Review*, 2) *Average % Positive Words*, and 3) *Average % Negative Words*. We include expert fixed effects in all the regressions. The relation between content of reviews and expert experience, proxied by *Ln (# of Days Since First ICO Review)* is reported in Panel A; community feedback proxied by *Ln (Number of Likes)* is reported in Panel B; and the combination of experience and community feedback in Panel C.

	(1)	(2)	(3)
Panel A: Expert Experience: Number of Days Since the First ICO Review			
	Average Number of Words	Average % Positive Words	Average % Negative Words
Ln (# of Days Since the First ICO Review)	8.633***	-1.067***	0.150
	(2.83)	(-3.56)	(1.60)
Observations	4574	4574	4574
Adjusted R-squared	0.372	0.319	0.100
Expert FE	Yes	Yes	Yes

Panel B: Community Feedback: Number of Likes from Previous Review			
	(1)	(2)	(3)
	Average Number of Words	Average % Positive Words	Average % Negative Words
Ln (Number of Likes)	3.264	-0.947*	-0.003
	(1.16)	(-1.87)	(-0.02)
Observations	4261	4261	4261
Adjusted R-squared	0.370	0.311	0.102
Expert FE	Yes	Yes	Yes

Panel C: Combined Impact of Experience and Community Feedback			
	(1)	(2)	(3)
	Average Number of Words	Average % Positive Words	Average % Negative Words
Ln (Number of Likes)	2.076	-0.773	-0.020
	(0.72)	(-1.59)	(-0.11)
Ln (# of Days Since the First ICO Review)	13.811***	-2.014***	0.203
	(2.96)	(-4.31)	(1.44)
Observations	4261	4261	4261
Adjusted R-squared	0.377	0.324	0.103
Expert FE	Yes	Yes	Yes

Table 8B
Impact of Expert Experience and Community Feedback on Numerical Ratings

The table shows the relation between the expert numerical ratings and prior experience (Panel A) and community Feedback (Panel B), and combined impact of prior experience and community feedback. The numerical ratings cover three categories: 1) *Average Rating-Team*, 2) *Average Rating-Product*, and 3) *Average Rating-Vision*. We include expert fixed effects in all the regressions. The relation between the expert numerical ratings and expert experience, proxied by *Ln (# of Days Since First ICO Review)* is reported in Panel A; community feedback proxied by *Ln (Number of Likes)* is reported in Panel B; and the combination of experience and community feedback in Panel C.

	(1)	(2)	(3)
Panel A: Expert Experience: Number of Days Since the First ICO Review			
	Average Rating-Team	Average Rating-Product	Average Rating-Vision
Ln (# of Days Since the First ICO Review)	-0.017	-0.004	-0.027
	(-0.92)	(-0.18)	(-1.30)
Observations	4574	4574	4574
Adjusted R-squared	0.238	0.281	0.274
Expert FE	Yes	Yes	Yes
Panel B: Community Feedback: Number of Likes from Previous Review			
	(1)	(2)	(3)
	Average Rating-Team	Average Rating-Product	Average Rating-Vision
Ln (Number of Likes)	-0.052	-0.064**	-0.078**
	(-1.63)	(-2.18)	(-2.31)
Observations	4261	4261	4261
Adjusted R-squared	0.240	0.286	0.281
Expert FE	Yes	Yes	Yes
Panel C: Combined Impact of Experience and Community Feedback			
	(1)	(2)	(3)
	Average Rating-Team	Average Rating-Product	Average Rating-Vision
Ln (Number of Likes)	-0.051	-0.062**	-0.075**
	(-1.63)	(-2.17)	(-2.28)
Ln (# of Days Since the First ICO Review)	-0.012	-0.015	-0.040
	(-0.44)	(-0.53)	(-1.34)
Observations	4261	4261	4261
Adjusted R-squared	0.240	0.286	0.282
Expert FE	Yes	Yes	Yes

Table 9
The Impact of Experience in an Industry and Content of Reviews

The table shows the relation between the content of expert reviews and their experience in the ICO's industry. The content of expert reviews is proxied by *% Positive Words*, *% Negative Words*, and numerical ratings on team, product and vision. Panel A includes expert fixed effects, and Panel B includes ICO fixed effects. *Expert Common Categories* equals the number of categories of ICOs in which the expert is a team member that overlaps with the categories of the ICO being reviewed. An expert may be associated as a team member or an advisor.

	(1)	(2)	(3)	(4)	(5)
Panel A: Expert Common Category with Expert Fixed Effects					
	% Positive Words	% Negative Words	Rating-Team	Rating-Product	Rating-Vision
Expert Common Categories	0.024	-0.017**	0.004***	0.004***	0.004***
	(1.51)	(-2.55)	(3.21)	(2.92)	(2.88)
Constant	24.703***	4.711***	3.806***	3.514***	3.771***
	(143.24)	(64.29)	(229.08)	(209.04)	(224.02)
Observations	8401	8401	14060	14060	14060
Adjusted R-squared	0.327	0.080	0.178	0.205	0.186
Fixed Effects	Expert	Expert	Expert	Expert	Expert
Panel B: Expert Common Category with ICO Fixed Effects					
	% Positive Words	% Negative Words	Rating-Team	Rating-Product	Rating-Vision
Expert Common Categories	0.145***	-0.016**	0.000	0.003**	0.003***
	(3.52)	(-2.23)	(0.33)	(2.27)	(3.32)
Constant	23.413***	4.697***	3.856***	3.532***	3.788***
	(29.92)	(27.15)	(135.57)	(89.39)	(93.00)
Observations	8401	8401	14060	14060	14060
Adjusted R-squared	0.154	0.247	0.475	0.386	0.390
Fixed Effects	ICO	ICO	ICO	ICO	ICO

Table 10
LDA Topic Analysis of Expert Textual Reviews

We perform topic analysis using Latent Dirichelet Analysis (LDA) on all the textual reviews. The number of topics is set to five for the estimation of our topic model. This table presents the top 10 terms for each of the five individual topics generated by the LDA.

LDA topics
The top words of the 5 topics:
Topic 1 *ICO (or security)*: ico, market, company, working, crypto, space, cap, world, idea, hard
Topic 2 *Blockchain or platform*: see, blockchain, project, mvp, projects, people, platform, lot, icos, technology
Topic 3 *Product/vision*: product, vision, good, interesting, project, idea, really, investors, best, whitepaper
Topic 4 *Team*: team, good, great, project, strong, vision, advisors, experience, luck, kyc
Topic 5 *Token/Information/White paper*: token, project, ico, get, tokens, information, time, website, whitepaper, business

Table 11
Determinants of Funds Raised by ICOs

The table reports the relation between expert reviews and funds raised in an ICO. The dependent variable is the logarithm of the funds raised in an ICO. The main independent variables of interest are Sentiment-All, Sentiment-Team, and Sentiment-Vision, generated by the Valence Aware Dictionary and Sentiment Reasoner (VADER). Sentiment-All is generated based on all the sentences in the textual reviews. Sentiment-Team is generated based on the sentences related to team. Sentiment-Vision is generated based on the sentences related to vision. Sentiment-Product is generated based on the sentences related to product. All the other independent variables are defined in the previous tables. We include dummies for platform, category (industry), currency of payment accepted, and country from which the ICO is issued.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sentiment-All	0.568***						
	(3.37)						
Sentiment-Team		0.688***			0.410**		
		(3.51)			(1.97)		
Sentiment-Vision			0.690***			0.466**	
			(3.64)			(2.51)	
Sentiment-Product				0.813***			0.509**
				(4.34)			(2.57)
Rating-Team					0.225***		
					(2.70)		
Rating-Vision						0.236***	
						(2.94)	
Rating-Product							0.224***
							(3.02)
Benchy Rating					0.378***	0.367***	0.373***
					(2.88)	(2.82)	(2.83)
Number of Team Members	0.032***	0.031***	0.031***	0.031***	0.024***	0.026***	0.026***
	(4.59)	(4.50)	(4.48)	(4.45)	(3.33)	(3.66)	(3.63)
Minimum ISS Score of Team Members	0.165***	0.167***	0.172***	0.166***	0.141***	0.141***	0.137***
	(6.85)	(7.19)	(7.47)	(7.27)	(6.12)	(5.94)	(5.93)
KYC Registration	-0.205	-0.209	-0.210	-0.188	-0.244	-0.271	-0.245
	(-1.24)	(-1.25)	(-1.26)	(-1.14)	(-1.46)	(-1.64)	(-1.49)
Whitelist Registration	0.172	0.193	0.163	0.177	0.182	0.184	0.193
	(1.10)	(1.21)	(1.04)	(1.12)	(1.15)	(1.18)	(1.22)
Number of KYC Successes	-0.201***	-0.195***	-0.196***	-0.205***	-0.310***	-0.302***	-0.312***
	(-3.08)	(-2.95)	(-3.01)	(-3.14)	(-4.22)	(-4.18)	(-4.27)
Number of Restricted Countries	0.000	-0.001	0.001	-0.000	0.002	0.002	0.003
	(0.06)	(-0.07)	(0.11)	(-0.04)	(0.22)	(0.29)	(0.33)
Platform dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Currency dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	853	853	853	853	853	853	853
Adjusted R-squared	0.166	0.162	0.163	0.166	0.181	0.184	0.185

Table 12
Divergence of Opinion and Funds Raised

The table reports the relation between expert divergence of opinion and funds raised in an ICO. The dependent variable is the logarithm of the funds raised in an ICO. The main independent variable of interest is Average Cosine Similarity. We include the ICOs with at least two textual reviews in this analysis. We first calculate the pair-wise cosine similarity for each pair of textual reviews within an ICO and then take the average of all the cosine similarities as the Average Cosine Similarity. All the other independent variables are defined in the previous tables. We include dummies for platform, category (industry), currency of payment accepted, and country from which the ICO is issued.

	(1)	(2)	(3)	(4)	(5)	(6)
Average Cosine Similarity	2.882**	2.757**	2.946**	2.809**	2.694**	2.867**
	(2.49)	(2.36)	(2.54)	(2.38)	(2.26)	(2.42)
Rating-Team	0.233*			0.220*		
	(1.92)			(1.81)		
Rating-Vision		0.287***			0.278***	
		(2.74)			(2.64)	
Rating-Product			0.231			0.219
			(1.56)			(1.48)
Benchy Rating				0.117	0.110	0.123
				(0.70)	(0.66)	(0.75)
Number of Team Members	0.017*	0.018**	0.019**	0.017*	0.018**	0.019**
	(1.95)	(2.24)	(2.28)	(1.91)	(2.19)	(2.23)
Minimum ISS Score of Team Members	0.223***	0.215***	0.221***	0.218***	0.211***	0.217***
	(4.68)	(4.60)	(4.53)	(4.52)	(4.46)	(4.39)
KYC Registration	-0.146	-0.149	-0.158	-0.151	-0.154	-0.164
	(-0.88)	(-0.92)	(-0.97)	(-0.91)	(-0.95)	(-1.00)
Whitelist Registration	0.120	0.129	0.128	0.115	0.122	0.122
	(0.74)	(0.80)	(0.79)	(0.71)	(0.76)	(0.75)
Number of KYC successes	-0.311***	-0.324***	-0.303***	-0.341***	-0.352***	-0.334***
	(-4.19)	(-4.44)	(-4.13)	(-3.93)	(-4.07)	(-3.89)
Number of Restricted Countries	-0.000	-0.000	-0.001	0.000	0.001	-0.001
	(-0.05)	(-0.01)	(-0.16)	(0.04)	(0.08)	(-0.06)
Platform dummies	Yes	Yes	Yes	Yes	Yes	Yes
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes
Currency dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	432	432	432	432	432	432
Adjusted R-squared	0.207	0.213	0.207	0.206	0.212	0.206