The Role of "Expert Reviewers" in Private Capital Markets

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Abstract

We study initial coin offerings (ICOs) to understand how an unregulated market overcomes information frictions and conflicts of interest. Listing platforms both independently assess an offering and crowdsource information from "expert" reviewers. These experts provide more balanced textual reviews as they gain experience and receive positive feedback from the community, consistent with a reputation effect. We find that proceeds are higher when reviews are more positive even after controlling for both the reviewer's and platform's numerical rating. Finally, experts with greater potential conflicts of interest are more positive than other reviewers, but investors identify these conflicts and discount their reviews.

Keywords: : Private Markets, Information Asymmetry, Capital Raising, ICO, FinTech

JEL Classifications: D82, G14, G20

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ABSTRACT

We study initial coin offerings (ICOs) to understand how an unregulated market overcomes information frictions and conflicts of interest. Listing platforms both independently assess an offering and crowdsource information from “expert” reviewers. These experts provide more balanced textual reviews as they gain experience and receive positive feedback from the community, consistent with a reputation effect. We find that proceeds are higher when reviews are more positive even after controlling for both the reviewer’s and platform’s numerical rating. Finally, experts with greater potential conflicts of interest are more positive than other reviewers, but investors identify these conflicts and discount their reviews.

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1. Introduction

The popularity of private markets such as crowdfunding highlights the appetite of retail investors to be involved in early stage financing. A prominent debate in the academic literature is whether access to these type of investments should be less restrictive. As the size of private markets grows, concerns have been raised by policy makers and others about the possibility of misinformation provided to investors, particularly those that are relatively unsophisticated. Due to data limitations, however, little is known about how private markets organize themselves to reduce information frictions and what solutions exist to reduce the probability of misrepresentation.

In this paper, we use the introduction of ICOs to understand whether private markets can self-organize to overcome information asymmetry and conflicts of interest in the absence of mandated disclosure and regulatory oversight. If so, our findings may be useful to regulators as they consider if it is prudent to expand the investor base for private offerings.[1]

In public markets, investors rely on legal sources such as company regulatory filings as well as information produced by intermediaries such as research analysts and auditors to obtain knowledge about the offering. Private market participants, such as those in the ICO market, do not have access to such information.[2] In the ICO market, platforms such as ICObench, may fill this void by overseeing and providing information to investors. In addition to the metrics produced by the platform itself, ICObench relies heavily on voluntary "experts" to crowdsource information about the quality of the offering. To provide oversight on the reviewer content, ICObench rates the quality of the expert by how well they meet certain criteria. Thus, the platform helps overcome information asymmetry by certifying certain aspects of the offering as well as overseeing the information production by experts.

[1]Generally, participation in private securities offerings is limited to accredited investors. Recently, the SEC expanded the definition of accredited investor but kept the income thresholds the same as they were in 1983. Not everyone was in favor of maintaining the status quo: "Consumer Federation of America Director of Investor Protection Barbara Roper, claimed that the Commission's refusal to raise the thresholds allows private issuers to remain free to peddle their securities to people who do not have access to essential information about the investments." https://www.forbes.com/sites/tedknutson/2020/08/26/sec-gives-more-retail-investors-access-to-private-funds-companies/#5374e1bfa4a9.

[2]Recently, the Securities and Exchange Commission (SEC) suggested that many ICOs may be considered securities and therefore, must follow rules for private offerings (https://www.sec.gov/news/public-statement/statement-clayton-2017-12-11). These rules generally restrict sales of securities to accredited or sophisticated investors and only require disclosure if any non-accredited investor is allowed to participate. Since token offerings are primarily targeted to retail investors (Fahlenbrach and Frattaroli (2020)), the main impediment for complying with securities laws is the inability to sell a significant fraction (or any, depending on the exemption) to non-accredited investors.

The literature has shown that the numerical ratings produced by experts affect ICO outcomes. For example, Lee, Li, and Shin (2019) suggest that the role of experts in the ICO market could substitute for the role of due diligence done by underwriters in IPOs. Bourveau, De George, Ellahie, and Macciocchi (2019), and Lee, Li, and Shin (2019) find that the numerical ratings of reviewers are related to both the success of the offering and the long-run performance in the aftermarket. Florysiak and Schandlbauer (2019) show that the higher the reviewer numerical rating, the lower is the probability of fraud. In a contemporaneous paper, Barth, Laturnus, Mansouri, and Wagner (2020) document that when an ICO has more reciprocal reviews, it is more likely to fail.

Experts, however, provide more than numerical ratings about the project. In many cases, they provide a written review prior to the ICO completion date with a discussion of the offering, management team, business model, and likely success. These narratives are richer than the quantitative rating and likely incorporate both the expert's experience and any voluntary disclosure by the issuer. Our contribution is to better understand the information in these textual reviews over and beyond the numerical ratings provided by experts and other third party vendors. We use machine learning to categorize the content of the review and then test if narrative content affects ICO outcomes after controlling for the numerical rating. Many of these reviewers are themselves involved in ICOs and/or wish to be hired as an advisor to an ICO team. Therefore, we analyze if conflicts of interest affect a reviewer's textual content, and whether market participants are able to recognize these conflicts.

Although expert opinions in the ICO market have some commonalities with consumer ratings in product markets, they differ on a number of dimensions. First, the experts we study are themselves rated by the platform, thus allowing investors to discriminate between experts. Second, not all consumers have experience with a particular product but may not have expertise across many products. Experts in the ICO market often rate many offerings and therefore, are able to accumulate knowledge over time. Finally, to our knowledge, the ICO market is the first private financial market to utilize voluntary individuals as experts in a concerted fashion.

Our initial sample contains 4,345 ICOs from ICObench.com issued between 2015 and 2018. Expert reviewers provide numerical ratings for 2,296 and textual reviews for 1,578 of these ICOs, for a total of 7,930 textual reviews written by 384 experts. For offerings with at least one textual review, there is an average of approximately five experts per offering, indicating that reviewers are active in this market.[3]

We use a number of linguistic algorithms to understand the textual content of the reviews. In order to make our textual reviews comparable to the category of the expert's numerical ratings, we use the key words "vision", "product", and "team" to classify each sentence in the review. In addition, we confirm using Latent Dirichelet Allocation (LDA) that these three terms are also strongly present as topics in the review corpus. In addition, for each sentence in the review, we apply Stanford Natural Language Processing (SNLP) to the textual reviews to determine the sentiment of the reviews as positive, negative, or neutral.[4] We use SNLP to generate an overall sentiment score as well as sentiment scores on each of the three topics. We find that the correlation between the content of numerical ratings and textual reviews is only 40% indicating that textual reviews incorporate additional information that may be useful to investors.

Our analysis begins with an exploration of what determines whether an expert will provide a textual review in addition to their numerical ratings. (An expert may decide to only provide a numerical rating but not a review. However, she cannot provide a review without a rating.) Both the presence and number of expert reviewers are increasing in the number of team members in the offering and the number of team members who provide identifying information about themselves to ICObench. In addition, ICOs that have a higher algorithmic Benchy rating are more likely to receive a textual review and to have more reviewers. These characteristics suggest that reviewers are attracted to offerings that may have higher visibility and potential quality.

Given that an expert decides to rate an offering, we are interested in what factors motivate her to write a review. We hypothesize that both feedback from the community and the reviewer's experience will be important predictors of whether the expert decides to write a textual review in addition to her numerical rating. Indeed, our results support this conjecture. Controlling for the type of reviewer using expert fixed effects, we find that experts are more likely to provide a narrative for a subsequent offering if they have received more "agrees" from the community and have a larger number of prior reviews. This effect is non-trivial. For example, a one standard deviation increase in the reviewer's experience is associated with a 7.6% higher probability that the expert will provide a textual review on the next offering she rates. Positive review feedback has a

[3]We use experts and reviewers interchangeably throughout the paper.

[4]Unlike other sentiment prediction systems that look at words in isolation, this deep learning model takes into account whole sentences based on the sentence structure. Sentiment is based on how words compose the meaning of longer phrases. Thus, it is not a bag of words approach.

similar effect, raising the probability of a textual review by 7.1%.

We find that as experts gain experience and receive positive feedback, their reviews become less positive, consistent with a reputation effect that incentivizes experts to continue providing textual content. This result holds using reviewer fixed effects and controlling for the quality of the offering. Consistent with the literature, such reputation effects improve the quality and reduce the biases in the experts' opinions (Shapiro (1983)).

In order for the narrative component of reviews to be useful, they should be correlated with ICO outcomes. Following the literature (e.g., Bourveau, De George, Ellahie, and Macciocchi (2019); Florysiak and Schandlbauer (2019); and Lee, Li, and Shin (2019)), we examine whether textual content adds predictive power in determining the amount of proceeds raised over and above the numerical rating provided by experts and the platform's own metrics. We find that the more positive the narrative review, the greater the funds raised. This holds true for each of the individual components of the review such as team, vision, or product. For example, an increase of one standard deviation in the average sentiment in the review related to the team, vision, or product is associated with 25%, 20%, and 30% more funds raised in the cross-section of offerings.[5]

Using cosine similarity, we examine whether reviewer consensus in the narrative about the ICO affects the amount of proceeds raised. We document that the greater the content similarity of the reviews for a particular offering, the greater the proceeds raised. On the other hand, we do not find a similar result when there is consensus in the numerical rating (or sentiment score). 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 offerings. Overall, these findings suggest that the information produced by the experts in their textual reviews is indeed important to investors and significantly affects the funding outcome.

An important contribution of our analysis is to examine whether the potential for conflicts of interest affects the reviewers' textual content. Potential for conflicts of interest can be quite severe in this market because expert reviewers are often themselves advisors and team members of other ICOs. Even in public equity markets that require substantial disclosure, conflicts of interest in analyst recommendations have been documented by Michaely and Womack (1999). Similar

[5]Similarly, an increase of one standard deviation in the numerical rating related to team, vision, and product is associated with 36%, 38%, and 29% more funds raised in the cross-section of offerings, respectively.

concerns have been raised in the ICO market about biases in experts' narrative. For example, medium.com commenting on the divergence between the reviewers' numerical assessment and the Benchy rating, notes that "the discrepancy between these ratings highlights how enormous the potential bias of individual expert reviewers can be."[6]

We measure the potential for conflicts of interest by the reviewers' direct and indirect connections to the team members of the ICO. A direct connection is when the expert has been on the same team as any member of the ICO's team before the expert provides a review. The number of potential indirect connections is proxied by the number of ICO team members in our sample that an expert has worked with in other ICOs. Experts with either a strong connection to the ICO team or more connections to team members in general, write more positive (and less negative) reviews even when controlling for ICO or reviewer fixed effects. In other words, within an ICO, connected experts write more positive reviews and the greater the connections of the expert, the more positive is the review. Thus, these results point to a potential bias in the ratings of connected reviewers.[7]

Our final analysis is to ascertain whether investors can discriminate between potentially biased and unbiased reviews. Comparing the effect of the average sentiment score of reviews for experts with high indirect connections with experts with low indirect connections, we find that investors appear to discount the reviews of potentially conflicted experts. We show that the sentiment of reviews of experts with greater connections (more conflicted) does not affect the proceeds raised. In contrast, proceeds are increasing in the positive sentiment of reviews for reviewers with low (or no) connections to the ICO's team. This suggests that investors discount the more positive (and less informative) reviews of highly connected experts and focus on those that do not have a potential prior relationship with the team. These findings point to the benefit of the platform's oversight of their experts. By providing transparency around the expert's activities as well as an assessment of how well the expert meets certain criteria, investors can use the platform to identify potentially higher quality offerings.

Our study adds to a rapidly growing literature on ICOs. New markets for capital formation are rare and thus interest in the ICO market has generated a number of studies that seek to understand

[6]https://medium.com/revain/the-ico-expert-and-community-rating-ecosystem-642b4475773d.

[7]An alternative hypothesis for the experts' connection with ICO teams is that these connected experts might have more information about the ICO teams and thus their reviews might be more informative. However, our empirical evidence does not support this alternative hypothesis. In particular, we find the connected experts' reviews to be shorter and more positive on average.

how this market functions (Adhami, Giudici, and Martinazzi (2018), Amsden and Schweizer (2018), Benedetti and Kostovetsky (2021), Canidio (2020), Catalini and Gans (2019), Chod and Lyandres (2021), Lyandres (2019), Cong, Li, and Wang (2021), Roosenboom, van der Kolk, and de Jong (2020), Dittmar and Wu (2019), Fisch (2019), Howell, Niessner, and Yermack (2020), Hu, Parlour, and Rajan (2019), Huang, Meoli, and Vismara (2020), Li and Mann (2018), Lyandres, Palazzo, and Rabetti (2020), Momtaz (2020), and Sockin and Xiong (2020)). We also contribute to the literature that documents the existence of conflicts of interest in analyst ratings even in regulated public markets, (see Michaely and Womack (1999), Kolasinski and Kothari (2008), O'Brien, McNichols, and Hsiou-Wei (2005), and Mehran and Stulz (2007) to name a few). Finally, our paper adds to the emerging social finance literature (Hirshleifer (2020), Han, Hirshleifer, and Walden (2021), Kuchler, Li, Peng, Stroebel, and Zhou (2020), Bali, Hirshleifer, Peng, and Tang (2018), among others) by examining the role of connections and feedback in experts' reviews.

2. Data

We obtain data on 4,345 offerings 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" and claims to be the number one ICO rating platform.[8] As an indication of the quality of the platform, Lyandres, Palazzo, and Rabetti (2020) examine differences across ICO aggregators and note that ICObench tends "to provide relatively high quality data." In their sample of aggregators, they also find that ICObench covers the most ICOs.[9]

As part of the service provided to issuers, the platform collects and publishes information on ICOs including business description, attributes of the team, offering characteristics, and a variety of data related to the issuer. For example, the data includes information on how the offering is sold, country of origin, links to other information sources such as Twitter or Facebook, whether the ICO has a white paper, currencies accepted, and the blockchain used. In addition, it assesses the quality of the ICO by publishing its own quantitative metrics including the platform's own algorithmic ratings (Benchy), as well as ICO success scores of the issuer's team members. More importantly, it crowdsources numerical ratings and narrative reviews from a variety of experts. We

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

[9]Other studies that have used the data from this platform include Howell, Niessner, and Yermack (2020), Lyandres, Palazzo, and Rabetti (2020), and Benedetti and Kostovetsky (2021).

collect this information via the platform's Application Programming Interface (API).

2.1 Offering and issuer summary statistics

Table 1 presents summary information on the main variables of interest in our sample of offerings and Appendix A.1 defines all variables used in this study. On average, an offering raises $17.1 million, however, the median is smaller at $5.02 million. Even though the largest offering in our sample is Block.one's EOS raised $4.2 billion, only 18 offerings in our sample raise $100 million or more. It should be noted that proceeds for many offerings are not reported and it is unclear whether this is because the data is unavailable, or the offering was not completed.[10] Thus, in a few of our tests, we restrict the analysis to only those offerings that report proceeds raised.

Some ICOs state the minimum and maximum amount of proceeds they wish to raise. The average minimum (soft cap) is $5 million and the average maximum (hard cap) is $47 million. On average (median), it takes an average of 57 (median is 36) days to complete an offering.

As the ICO market was currently unregulated during our sample period, issuers were not required to provide any disclosure documents to investors.[11] However, almost all of the issuers in our sample provide a link to a white paper. These white papers describe the problem the project is to solve, the type of product the issuer will produce, the management team, the number of tokens to be sold, the amount of funds to be raised, and the use of funds. To capture whether the issuer voluntarily provides a white paper, we use an indicator variable equal to one if there is a link to a white paper provided, zero otherwise. As can be seen in the Appendix A.2, 96% of issuers have a link to a white paper.

Like analysts in public offerings who distill regulatory filings for investors, experts are likely to use the content of the white paper in their review. As noted in the media, some issuers have been found to simply copy white papers of prior ICOs and therefore, reviewer scrutiny of these documents may highlight problematic offerings.[12] Florysiak and Schandlbauer (2019) use textual

[10] There are 1,296 ICOs with non-missing values for funds raised. In cases where proceeds are missing, we attempt to find any available information on the offering through a web search for news stories and/or the company's website.

[11] Even if the offering is an STO, there is no disclosure requirement to accredited investors. Should unaccredited investors participate in the offering, the issuer "must give any non-accredited investors disclosure documents that generally contain the same type of information as provided in registered offerings (the company is not required to provide specified disclosure documents to accredited investors, but, if it does provide information to accredited investors, it must also make this information available to the non-accredited investors as well)". See https://www.sec.gov/smallbusiness/exemptofferings/rule506b for more information.

[12] For example, claims have been made that the TRON ICO copied Filecoin's white paper

analysis to determine when the white paper has new and/or informative content and finds mixed evidence on the importance of informative content in predicting proceeds. They suggest that one reason is that "if the weight on expert ratings becomes sufficiently large, the impact of informative white paper content vanishes."

As will be shown in later tests, the team, both its quality and its relationship to the reviewer, is an important factor influencing the outcome of the offering. On average, an offering has 13 team members with a median of 12.[13] We also include a number of additional offering characteristics related to the platform, links to other information, country of origin, and investor requirements that are used as control variables in our tests. Summary statistics for these variables are in Appendices A.2 and Appendix A.3.

2.2 Platform metrics

As part of its oversight of listings on its website, ICObench provides a number of metrics that are designed to measure the quality of certain aspects of each offering. The first metric is an automated algorithm, referred to as Benchy, that evaluates each offering on 20 different criteria. The algorithm provides a rating on a scale of 1 to 5 (with 5 being the best) for each offering based on the following characteristics: team, ICO information, product representation, and marketing/social media. Information on ICObench's website provides some indication of how the ratings are determined. Teams that have participated in multiple offerings are considered more trustworthy. Product representation is based on the availability of information contained in white papers and video presentations. Marketing/social media captures how in touch the ICO team is with potential investors. In order to compare expert ratings to the Benchy algorithm, Table 2 shows statistics on the Benchy rating, for the 2,296 ICOs that have at least one numerical expert rating. The mean and median Benchy ratings are 3.33 and 3.40, respectively.

In addition to the ratings algorithm, ICObench collects the number of management team members that voluntarily provide identifying KYC information to the platform. (ICObench states that any suspicious ICOs will need to go through the KYC procedure.) The issuer provides the name of team members to ICObench and then the platform selects at least two members to pass through

(https://coincentral.com/community-accuses-tron-plagiarizing-whitepaper/)

[13]Given the importance of the team in predicting the amount of proceeds raised, it is not surprising to hear of allegations that some ICOs inflate the number of team members or misrepresent the composition of the team. See https://www.bluebelt.asia/the-three-easiest-indicators-of-an-ico-scam/.

the KYC procedure. The platform then notes the number of team members that successfully pass the its KYC requirement, *Number of KYC Team Successes*. The average ICO has approximately 50% of its team members passing ICObench's KYC requirement but the median ICO has none.

Finally, ICObench assigns a second rating to each team member, *ICO Success Score (ISS)*, based on whether or not they have been associated with other successful ICOs. The success of an ICO is determined by the amount of funds raised, whether the ICO is exchange-traded, and the return on investment.[14] As an example, on July 26, 2019, Ian Scarffe was listed as having the highest ISS of 216.2.[15] On his LinkedIn profile, his title is "Blockchain – ICO/STO Advisor/Consultant/Strategist/Investor" and he notes that he is an advisor to several ICOs. In Table 2, we document that the mean and median ISS scores for the team are 7.56 and 4.35, respectively. The average of the minimum ISS score among the ICO teams is 2.76 and the maximum is 46.25.

3. Expert numerical ratings

Individuals who wish to serve as experts must apply to the ICO platform. In order to do so, ICObench requires the following:

> "Any ICObench user with a fully updated profile (full name, photo, set profile URL, title, bio, location, and a LinkedIn link) 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."

These experts provide ratings on a voluntary basis and because the information provided by experts is one of the primary services provided by the platform, ICObench monitors their content and reputation. As will be examined in greater detail later, ICObench incentivizes reviewers to meet certain criteria in order to improve their standing in the community. These criteria include passing the KYC procedure, their own ISS score, how long they have been active, and whether or not they provide a narrative review in addition to their numerical rating. In addition, the platform tries to minimize conflicts of interest by declaring a number of criteria that may cause the expert

[14] ICObench provides a detailed breakdown of the team KYC procedure and how ISS score is determined at https://icobench.com/faq.

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

to be in violation of its principles. For example, the platform forbids payment for reviews, rating or reviewing ICOs that the expert participates in, and/or giving a competitor a bad rating.

If an expert decides to participate in providing information on an ICO, at a minimum, she assigns a numerical rating of 1 (lowest) to 5 (highest) to each of three characteristics of an offering: team, vision, and product. In order to maintain consistency with the platform's algorithmic rating, ICObench encourages experts to incorporate the same criteria used as input to the Benchy rating in their ratings: the team ranking should consider whether the members have participated in other related projects and/or they keep the community informed about the project progress, the vision ranking should be based on the objectives of the project, its market potential, and the business strategy, and the product rating should consider the stage and the technology behind the product, strategy and growth options, and commitment to understanding the market.

Our sample includes 458 unique experts and some of these experts participate in hundreds of ICOs. Appendix A.4 presents the top 25 most active experts in our sample who provide numerical ratings for between 127 and 582 ICOs apiece. Although not required, some experts may provide a textual review of the ICO. This means that all ICOs with textual reviews have a numerical rating but not all ICOs with a numerical rating have a textual review. Thus, the percentage of ICOs with both numerical and textual reviews varies by reviewers: some provide a textual review for every ICO and others provide none.

Table 3 shows the average numerical ratings given by experts on team, vision, and product for the 2,296 offerings with numerical ratings. (Out of these 2,296 offerings, there are 1,578 offerings with at least one textual review.) To avoid look ahead bias, we drop any numerical rating given or textual review written after the ICO end date from our sample. The mean overall rating on a five-point scale for all ICOs is 3.3. The ratings for each of the categories of team, vision, and product are 3.42, 3.45, and 3.18, respectively. In the case of EOS, eight experts provided ratings with weighted average ratings of 4.9 for team, 4.7 for vision, and 4.6 for product.

As shown in Appendix A.5, an example of a prolific reviewer is Hung Chih (Jason Hung) who is based in Canada.[16] According to ICObench, he has participated in 45 ICOs as an advisor, and rated 241 offerings (230 in our sample) with an average rating of 3.8 (slightly over the mean) out of 5. In our sample, he provides textual reviews for 64% of the ICOs he rates.

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

Despite the fact that the average reviewer's ratings in each category are similar to the algorithmic Benchy rating, we document only a 50% correlation between Benchy and experts' numerical ratings (untabulated). This finding is consistent with Bourveau, De George, Ellahie, and Macciocchi (2019) who show that the algorithmic ratings of ICOs are more likely to capture information sources such as the issuer's social media presence, the availability of a white paper, and the release of technical code, while expert ratings focus more on the underlying technology, the team, and the characteristics of the project. When we analyze the incremental impact of reviewers' ratings, we also control for the information content of the platform's ratings of the ICO and the team.

4. Expert textual reviews

In order to "read" close to 8,000 reviews and compare the numerical rating to the textual content of the review, we use a number of tools. First, we categorize the sentiment of each sentence of each review. Because the content of expert reviews are more similar to customer reviews on retail products and not the typical financial disclosure of regulatory filings, we do not use the Loughran and McDonald (2011) financial term dictionary to classify positive and negative sentiment for each review. Instead, we classify the sentiment of the review using the Stanford Natural Language Processing (SNLP) to generate positive and negative sentiment. The SNLP system is based on work by Socher, Perelygin, Wu, Chuang, Manning, Ng, and Potts (2013) and is designed to improve the classification of sentiment from short comments such as those posted on social media. The SNLP website notes the benefit of using SNLP as follows:[17]

> "Most sentiment prediction systems work just by looking at words in isolation, giving positive points for positive words and negative points for negative words and then summing up these points. That way, the order of words is ignored and important information is lost. In contrast, our new deep learning model actually builds up a representation of whole sentences based on the sentence structure. It computes the sentiment based on how words compose the meaning of longer phrases. This way, the model is not as easily fooled as previous models. For example, our model learned that funny and witty are positive but the following sentence is still negative overall: *This movie was actually neither that funny, nor super witty.*"

[17] https://nlp.stanford.edu/sentiment/.

Thus, SNLP is an improvement over the bag of words methodology used in Loughran and McDonald (2011), because it utilizes the positioning of words in a phrase to determine its sentiment.[18]

The initial dataset used in Socher, Perelygin, Wu, Chuang, Manning, Ng, and Potts (2013) is from voluntary movie reviews. While the context is different, the colloquial nature of expert's reviews of ICOs is similar to those in other voluntary review settings. The methodology first employs a training dataset of human decisions on the sentiment of movie review sentences and then uses this dataset in a recursive multiple-layer neural network to characterize the sentiment of much larger corpus. For example, the methodology can distinguish between these two sentences "Unlike the surreal Leon, this movie is weird but likeable" and "Unlike the surreal but likeable Leon, this movie is weird". This illustrates the power of word positioning.

The output of this exercise is a probability vector that determines how positive, negative, or neutral a given sentence is on a scale from 0 (most negative) to 4 (most positive). We transform this scale from 0 to 4 to 1 to 5 in order to be consistent with the scale of the numerical ratings of both experts and Benchy on ICObench.

For our data, we first classify every sentence in the data using three key words (team, vision, product) that mirror the three categories of numerical ratings. (As a check, we employ Latent Dirichelet Allocation (LDA) to determine if these three keywords are supported by topic modeling. As can be seen in Appendix A.6, these three words are highly present in the review corpus.) For each review of an ICO by an expert, we calculate the average sentiment of the narrative content weighted by the number of words in each sentence for the group of individual sentences that have a specific key word (*Sentiment-Team*, *Sentiment-Vision*, and *Sentiment-Product*). We also calculate an overall sentiment for the entire review, *Sentiment-All*, using the same method but incorporate the sentiment of all sentences in the review, not just those related to the keywords. To generate an overall score for an ICO across reviewers, we average each type of sentiment weighted by the number of words in each review.

In Appendix A.7, we provide some examples of sentences in the corpus that relate to each of the three attributes. In addition, we report the SNLP sentiment score for the entire review using all sentences and SNLP sentiment score for each topical sentence. The appendix also presents the numerical ratings the expert gave the ICO. The examples show that experts express different

[18]Babolmorad and Massoud (2020) discuss challenges with the bag of words approach.

opinions on different aspects of the offering. One thing to note is that the overall SNLP review score may not necessarily be in line with the sentence. Since we only present one sentence of the review, that particular sentence maybe negative for example, but the overall review could be positive.

Another thing to note about the table is that there can be a dichotomy between the SNLP overall sentiment score of the reviewer and her numerical rating. This could be due to the expert's desire to provide positive feedback even though the textual review is negative, for example, or the textual content captures only one aspect of the review and not the overall view of the expert. Thus, it is an empirical question whether and which type of textual information contributes to the information environment of the ICO over and above the numerical rating.

Table 4 presents the summary statistics on the textual reviews. In Panel A, we show summary statistics at the review level based on 7,930 textual reviews contributed by 384 experts. On average, an individual review consists of 71 words and 4 sentences. The overall sentiment is 3.32 with 46% of sentences classified as positive, 23% negative, and 31% neutral.

As with reviews on other platforms, each textual review can receive an "Agree" by other people as is the case with "likes" on social media. On average, each review receives 2.53 agrees with a median of 1.[19]

In Panel B, we consolidate all the textual reviews at the ICO level. On average, for the 1,578 ICOs in our sample with at least one textual review, there are 5 experts per offering with a median of three experts. However, the standard deviation is quite high at 6.68. For example, the highest number of textual reviews for an offering in our sample is 75 for the Sharpay ICO.

On average, the total number of words in all reviews of an offering is 356 with a median of 147. The average overall sentiment of the reviews is slightly positive or neutral with a score of 3.13 out of 5 and consistent with this, the reviews contain more positive than neutral or negative sentences. The average percentage of positive sentences for a given offering is 39%, 28% are negative, and 33% are neutral.

In Panel C of Table 4, we break down the ICO sample by the number of experts providing textual reviews. The largest number of ICOs (544) have only one textual review. The number of offerings with 2 or 3 textual reviews is 406, and with 4 to 10 textual reviews is 433. There

[19] It is also possible to disagree but this information is not available via the API. A cursory examination of a number of ICOs indicates that disagrees are much less frequent than agrees.

are 195 offerings with more than 10 reviews. Interestingly, in this univariate analysis, the average amount of funds raised does not necessarily correspond with the number of experts. In fact, the lowest median proceeds raised are for offerings with the most experts. Not surprising, the average cumulative number of words for all reviews increases with the number of reviewers.

The highest percentage of negative sentences and the lowest overall sentiment score are for offerings with only a few experts. The percentage of positive sentences is 38% to 39% for ICOs with fewer than four reviewers, however, this number increases to 42% if there are more than 10 reviewers. Similarly, 28% to 31% of the review is classified as negative if there are fewer than four reviewers, and drops to 25% for ICOs with more than 10 reviewers. While the negative correlation between the number of reviewers and the use of negative/neutral sentiment could be an indication of the quality of the ICO, with better ICOs having more reviewers, it could also be due to the greater potential for conflicts of interest. We examine this possibility later in the paper.

5. Reviewer motivation and content sentiment

In this section, we examine what motivates reviewers to provide reviews and whether their experience and feedback from the community affect the sentiment of their textual review. We begin by examining which offerings are more likely to be covered by experts by constructing two dependent variables for each of the two different types of ratings, numerical and textual. The first is an indicator variable, *Expert Coverage*, equal to one if the offering receives at least one expert rating/review, and zero otherwise. The second is the log of the number of experts, *Ln(Number of Experts)*, that provide a rating for the sample of ICOs with at least one expert rating/review.

We include a number of independent variables related to the offering. The platform's own assessment of the offering is captured using the *Benchy Rating* as a control variable. (Our results are robust to including the overall ICObench numerical rating instead. The overall ICObench rating is combination of the experts' numerical ratings and the Benchy rating.) Bourveau, De George, Ellahie, and Macciocchi (2019) find that numerical rating provided by experts and the Benchy rating are not equivalent and argue that "algorithmic ratings capture *disclosure quantity*, whereas ratings by crypto experts provide assessments of the underlying quality of the ICO." Other platform metrics that capture the quality of the team included in the specification are the *Median ISS score of the Team Members*, and the number of team members passing the platform's KYC procedure, *Number of KYC Team Successes.*

Two indicator variables capture the requirements of investors in order to participate in the offering. The first is whether the investor is required to provide documentation or proof of identity in order to participate in an ICO (42% of offerings), *KYC Registration*, and second, if investors are required to register for the ICO in advance, *Whitelist Registration* (30% of offerings), which is less restrictive than *KYC Registration*. Finally, we include the *Number of Restricted Countries* where the offering cannot be sold. We also include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin.[20]

The results are presented in Table 5. Columns (1) and (2) show the determinants of numerical ratings while columns (3) and (4) show the determinants for textual reviews. Generally, the determinants for numerical ratings and textual reviews are similar. This is not surprising since textual reviews are conditional on the expert providing a numerical rating. We find that the platform's metrics are related to both the probability of an expert covering the ICO as well as the number of experts. Both the Benchy rating and the number of team members that pass KYC are positively related to the probability the ICO will have a rating or a review by an expert. Moreover, the greater the value of the metric, the larger are the number of experts that choose to participate. The median ISS score of the team is only positively related to the number of experts who rate the ICO. Thus, if the platform's metrics are correct, higher quality offerings are more likely to attract experts.

The presence of a white paper is negatively related to the number of experts who provide a rating or a review. This suggests a substitution effect between the disclosure of a white paper and the number of experts who are willing to put forth effort to evaluate the ICO. This is somewhat consistent with Florysiak and Schandlbauer (2019), and they find that the more informative the white paper, the fewer are the number of experts rating the offering. We do not find, however, that the availability of a white paper affects the probability that the ICO will be rated or reviewed.

We show that offerings with larger teams are both more likely to have an expert rating or review and to also have a larger number of experts participating. Impediments to the sale of tokens such as requiring investors to provide proof of identity reduces the probability and the number

[20]We confirm that the inclusion of these control variables in this and all other tables do not introduce multicollinearity by checking the variance inflation factors.

of experts providing a numerical rating. For textual reviews, the effect of requiring investors to register and/or provide proof of identity each have opposite signs making their interpretation less clear. Finally, we find mixed evidence that the number of restricted countries affects the probability of expert coverage or the number of experts who participate.

5.1 Reviewer motivation

For an expert, increasing one's reputational capital can reap a number of benefits both on ICObench and in the ICO community more generally. Having a high reviewer score from ICObench, as in the example of Jason Hung, elevates an expert's profile.[21] A greater profile on the platform will bring the reviewer to the attention of ICO teams who may hire him/her as an advisor. Measurable attributes somewhat under the reviewer's control that increase the ICObench expert score include whether the expert provided a textual review (30% of the overall score), the length of time the reviewer has been active (20% of the overall score) and the amount of community support, as indicated by the number of "agrees" a review receives (15% of the overall score).[22]

In order to understand what motivates an expert to voluntarily produce information, we examine whether the probability of a reviewer providing a subsequent textual review is due to the expert's prior experience (*Experience*) measured as the number of offerings the expert has reviewed and/or rated, [23] and/or the cumulative number of "agrees" the expert has received (*Positive Feedback*) in the time period leading up to the ICO.[24] In Table 6, the dependent variable takes the value of 1 if the expert provides at least one subsequent textual review on day t+1, and 0 if the expert only provides a numerical rating. In order to remove any concern that certain experts are more likely to provide a textual review due to their type, we include expert fixed effects in all specifications. In addition, in this and all subsequent tables, we include the same control variables and fixed effects as in Table 5.

In column (1), we show that the probability of providing a textual review for the next ICO is

[21] https://icobench.com/experts. The weighting score is applied when ICObench aggregates individual experts' ratings to the ICO level rating.

[22] Other attributes that we do not measure include their ISS score (15%), whether they passed a KYC procedure (5%), if their profile is complete (10%), and whether they contribute to the platform by providing feedback to ICObench (5%). For more information, see https://icobench.com/faq.

[23] Our results are robust if we substitute the time since the first rating for the cumulative number of reviews.

[24] ICObench's website also indicates that participants can "disagree" with the expert as well. This variable, however, is not available through the website's API. A cursory examination of random ICOs suggests that "agrees" far outnumber "disagrees".

positively related to the cumulative number of offerings reviewed. Therefore, the more the expert has been active in rating ICOs, the more likely that she will provide a subsequent textual review.

We next analyze whether positive feedback from the community acts as a motivator for the reviewer to provide a narrative review on the next ICO. The positive coefficient on the number of "agrees" since the expert began reviewing ICOs increases the likelihood that the expert will provide a textual review for the next ICO she rates.

In column (3), we combine expert experience and positive feedback to see if one or the other is a more powerful motivator in getting the reviewer to provide textual content in addition to a numerical rating. We find that the coefficients on both expert experience and feedback are statistically significant and positive and have roughly the same effect on the probability of providing a textual review. Note that the relationship between the platform metrics generally support the notion that better quality ICOs are more likely to receive a subsequent textual review. However, when both experience and positive feedback are included in the specification, the effect of the platform's metrics is diminished. The only significant variable is the number of KYC team successes. Collectively, these results suggest that the probability of a textual reviews is more likely when the expert has participated in rating other ICOs and when prior reviews are well received by the community. In addition, the results provide some confirmation of the platform's own expert scoring system that incentivizes reviewers to post textual content.

5.2 Review sentiment

The previous findings begs the question, however, whether a reviewer's experience and her community feedback impacts the quality of the information she produces, either positively or negatively. On the one hand, an increase in reputation may make the reviewer more conservative in her estimation of the ICO in order to preserve her reputation. On the other hand, if an expert's main purpose for reviewing and rating an ICO is to get the attention of ICO issuers to hire her as an advisor, then we might expect an increase in the positive bias of the reviews over time.

In Table 7, we examine whether community feedback and the expert's past experience affects the sentiment of her textual review for the next ICO. The dependent variables are the number of words used and the proportion of sentences in the review that are positive, neutral, or negative. In addition, we include the overall sentiment score of the review. These variables are averaged by day if an analyst provides textual reviews for multiple ICOs. We include reviewer fixed effects in order to capture the change in the sentiment of the textual review over time while holding the quality of the expert constant.

As the reviewer gains experience, their reviews tend to be longer. The content of their reviews also skew less positive. The coefficient on the percentage of positive sentences is negative while the coefficients on both the percentage of negative and neutral sentences in the review increase. Thus, reviewers appear to become more balanced in their textual reviews as they gain experience. Positive feedback from the ICO community does not appear to affect the sentiment of subsequent reviews.

However, this finding may be driven by the choice of ICO to rate as the review gains experience. In order to mitigate this effect, we include the platform's metrics as a measure of quality. The positivity of the review is greater (more positive sentences, fewer negative ones) the higher the Benchy rating but this does not mitigate the significance of the expert's experience.

Overall, the results in this section suggest that reputation concerns incentivize the continuation of voluntary review provision as well as the sentiment of the narrative. More importantly, such reputation effects potentially improve the quality and reduce the biases in the experts' opinions (Shapiro (1983)).

6. Textual review content and the success of an offering

In order to be valuable, the textual review content produced by experts on the platform must result in positive outcomes for issuers over and above other offering and platform characteristics. As mentioned in the data section, we use the key words "team", "vision", and "product", to categorize the content of the sentences in a review. These key words are selected because they capture the same attributes as those of the reviewer's numerical ratings. This allows us to directly compare the impact of an expert's textual sentiment and numerical rating on ICO proceeds. We hypothesize that the more positive (negative) the sentiment of the textual review, the greater (lower) proceeds raised.

We note that the content of textual reviews and numerical ratings are not perfectly correlated. In untabulated results, we find at the ICO level, a 40% correlation between the numerical rating and the sentiment score on product, a 54% correlation between the numerical rating and the sentiment score on team, and a 31% correlation between the numerical rating and the sentiment score on vision. In addition, the correlation between the Benchy rating and overall sentiment scores of textual reviews is only 40%. These correlations point to the potential for the narrative content to improve the decision-making of investors and the outcome of the ICO.

We begin in Table 8 by examining the marginal effect of each category of textual sentiment on proceeds raised, over and above both the expert's numerical ratings and the platform's metrics. We follow the methodology in prior tables but instead standardize the coefficients for ease of interpretation. Note that the sample size declines once we require that the ICO both discloses proceeds raised and has a textual review.[25] In untabulated results, we document that ICOs are more likely to report proceeds when they have a numerical and/or textual rating, higher Benchy ratings, and more team members with greater ISS scores. In other words, "better quality" ICOs as measured by ICObench metrics and the willingness of experts to review the offering are more likely to report (and possibly raise) proceeds. Our results, however, are unchanged if we include ICOs that report proceeds but may not have a numerical and/or textual review (sample size of 1227 ICOs). In this case, we set the rating and/or the sentiment score equal to zero.

Since there is a strong correlation between the different sentiment variables, we examine the effect of each on proceeds individually. The greater the average sentiment (more positive) of experts' reviews, on all aspects of the offering such as team, vision and product, the higher the proceeds raised. In terms of economic significance, an increase of one standard deviation in the overall average sentiment results in 25% additional proceeds raised in the cross-section of offerings.[26] Furthermore, a one standard deviation increase in the average sentiment related to reviews of the team, vision, and product is associated with 25%, 20%, and 30% additional funds raised in the cross-section of offerings, respectively. We also find a strong association between the average experts' numerical rating and proceeds raised. These results suggest that both quantitative and qualitative information in the expert's review of the ICO is correlated with ICO outcomes.

The platform's metrics are also related to how much funds an ICO raises. A higher Benchy score

[25]This decline in sample size is consistent with other studies.

[26]The dependent variables in the analyses are the logarithm of funds raised. Therefore, an increase of one in the standardized overall sentiment corresponds to 0.22 increase in the log(funds raised), which translates into 25%=exp(0.22)-1 increase in the funds raised. Similarly, an increase of one in the standardized Benchy rating is associated with 38% more funds raised in the cross-section of offerings.

and the quality of the team, as measured by the ISS success score, both increase proceeds. However, the number of KYC team successes is negatively related to proceeds although we do not have a rationale for why this may be. Although causality is difficult to determine, one interpretation is that both experts and the platform contribute to the success of the offering by providing information that allows an ICO to stand out among its peers.

We next examine whether consensus among reviewers affects proceeds raised. The literature outside finance has shown that consensus among reviewers is an important component in predicting outcomes. For example, Kim, Lee, and Hun (2015) find that consensus among reviewers is more important than the sequence in determining consumers' attitudes and intentions to stay at a hotel. We predict that a similar effect may be found in financial reviews. In other words, investors may assess the quality of an ICO as higher (or lower) if the narrative reviews discuss similar attributes of the offering.

We create a variable, *Consensus-Textual*, that measures how similar is the discussion of the ICO among all the textual reviews. To construct this variable, we first restrict the sample to ICOs with at least two textual reviews. We then create a vector of words used throughout the entire review corpus and populate the vector with the number of times each individual word appears in a review. Because the corpus contains many words, many of the elements in the vector are equal to zero.

We then calculate the cosine similarity between each pair of reviews for an ICO, as in Hanley and Hoberg (2010) and Hanley and Hoberg (2012). Cosine similarity compares the distance between two vectors, in our case, vectors of words used in a review. If two experts say almost identical things about an ICO, their cosine similarity will be close to one. If they say completely different things, their cosine similarity will be close to zero. To aggregate the cosine similarity to the ICO level, we average all of the cosine similarities across all pairs of experts that provide a textual review for the ICO.

As with the prior tables, we hold constant the numerical ratings of the experts in analyzing the effect of textual content. In Table 9, we find that the greater the consensus among experts, the higher the proceeds raised. This means that when experts agree about an ICO the proceeds are higher and when they disagree, proceeds are lower. 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 offerings. In untabulated results, we split the sample of ICOs into those with overall positive and negative sentiment and find that the relationship we document between sentiment and proceeds is mainly driven by ICOs with positive sentiment.

In addition to the textual consensus, we also include a measure of consensus in the numerical rating, *Consensus-Rating*, for each of the three categories: team, vision, and product. We measure consensus as the standard deviation of numerical ratings multiplied by -1 in order to make the interpretation of this measure consistent with the textual consensus. Thus, a lower standard deviation results in a higher *Consensus-Rating*, indicative of greater consensus among reviewers. As can be seen from the table, unlike the consensus in textual reviews, the consensus of numerical ratings related to team and product has no explanatory power in the amount of proceeds raised. The consensus of numerical ratings related to vision is positively associated with funds raised.[27]

In this specification, the Benchy rating no longer has any explanatory power although the ISS score of the team members is still significantly and positively associated with proceeds raised. The coefficient on the number of KYC team successes remains negative. We note that the sample size is much reduced due to the requirement that the offering have at least two narrative reviews and also report proceeds. Even so, combined with the prior tables, the overall conclusion is that the experts' opinions expressed through a textual review matter to the success of the offering.

7. Potential conflicts of interest

The preceding analysis indicates that reviewers' textual information is a strong predictor of the success of an offering as measured by the proceeds raised. The reputation of an intermediary is its most important asset. In the market for ICOs, a platform is only viewed as credible if it imposes rules governing behavior (and enforces them). Conflicts of interest among experts clearly reduce the efficacy of the review process as well as the reputational capital of the platform.

There have been complaints about ICO reviews being biased. In August 2019, the Securities and Exchange Commission (SEC) settled a case with a Russian firm, ICO Rating, for failure "to disclose payments received from issuers for publicizing their digital asset securities offerings."[28] The

[27]In untabulated results, replacing the cosine similarity measure of consensus with the standard deviation of the overall sentiment score as well as those for team, vision, and product, we find that only agreement in the product sentiment increases proceeds raised. The coefficients on the other two attributes are insignificant.

[28]https://www.sec.gov/news/press-release/2019-157.

press release notes that the "securities laws require promoters, including both people and entities, to disclose compensation they receive for touting investments so that potential investors are aware they are viewing a paid promotional item." Furthermore, there have been allegations that some reviewers actively solicit reviews for money.[29] ICObench responded to these allegations by saying: "We have zero-tolerance for sales of ratings. We always encourage our community members to report any abnormal activity or information on the paid review. Dozens of experts were already revoked for violating the rules."[30] Thus, one prohibition that ICObench both states in their online materials and enforces is an expert taking or demanding payment to provide a rating or review for an ICO.

Conflicts of interest are not limited to the sale of reviews. Experts may have conflicts that lead to bias in at least two other ways. First, experts may provide negative reviews for their competitors and second, reviewers who have relationship with the ICO team may be more likely to provide positive reviews.

In order to partially mitigate these biases, ICObench limits certain types of participation by experts that might lead to a conflict of interest. They state:

> "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."[31]

Thus, ICObench's policy expressly prohibits the first type of conflict of interest, giving a negative review to a competitor, but only partially prohibits the second type, participating in an ICO. What the policy does not address are situations in which the reviewer may have an affiliation, either direct or indirect, with a member of the ICO team but does not directly participate in the ICO itself. For example, the expert may have been an advisor on a prior ICO in which a current team member is affiliated. In addition, the expert may have a wide network of connections with other ICO team members that may create an indirect affiliation with a current team member.

[29] See https://medium.com/alethena/this-is-how-easy-it-is-to-buy-ico-ratings-an-investigation-13d07e987394.
[30] https://decrypt.co/8474/call-it-a-summer-bargain-pay-for-play-icobench-reviews-are-selling-at-juicy-discounts.
[31] https://icobench.com/faq#q-5-6.

7.1 Conflict of interest and review sentiment

We construct two measures to capture these relationships between the reviewer and the current ICO's team members. The first variable measures the direct connection to the ICO team. *Direct Connection* is an indicator variable equal to one if the expert has been on the same team as any member of the ICO's team in the time period prior to the offering, zero otherwise. We have 384 experts in our review level analysis, of which 128 (1/3 of the experts) provided a textual review on at least one ICO where they had a prior affiliation with a team member. Among the ICOs in our sample, approximately 30% of them have been supplied with a textual review from at least one expert with a former connection.

The second variable measures the indirect connection that a reviewer might have through her participation on many ICOs. *Indirect Connections* is defined as the log of the number of individual ICO team members that were also on the same team as the expert in all ICOs over the sample period. Even though the expert may not directly know an individual on the ICO, they may have an indirect connection through relationships with former team members who themselves may have a direct connection. Thus, a reviewer who has a large network of team members likely has many indirect connections, making it possible that the current ICO team knows someone with which the expert is familiar.[32]

Among the 384 experts that provide textual reviews in our sample, 233 of them have been a team member of other ICOs while 151 of them have never been part of an ICO team. For the 233 experts that are in the ICO team network, we find that, on average, the expert has been a team member on 7 ICOs (median is 3) and has 157 ICO team member partners (median is 76).[33] If conflicts of interest exist, then we expect that the greater the number of connections of the reviewer, the more positive will be her review.

To test this, we begin by examining whether the content of the reviews differs when the expert is more connected. Panel A of Table 10 shows the results for reviewers with a direct connection and Panel B for reviewers that have indirect connections. In columns (1)-(5) in each panel, we include ICO fixed effects to mitigate concerns that reviewers with greater connections are more likely to

[32]In untabulated results, our results are robust to using the reviewer's centrality measure generated from social network analysis, i.e. degree or eigenvector centrality of the expert in the ICO team member network.

[33]The difference between the mean and median suggests a skewness in these measures as a small number of experts have been involved in disproportionately large number of offerings.

rate better ICOs. In columns (6)-(10), we include reviewer fixed effects, as well as platform metrics to control for the quality of the ICO, to test whether the sentiment of her review changes when she is more connected to the team members of the ICO. Thus, we reduce endogeneity concerns that connected reviewers gravitate toward particular ICOs.

Regardless of whether we use direct or indirect connections, the results are similar. First, within an ICO, more connected reviewers tend to write shorter reviews perhaps because they have written these as favors to the ICO team and thus, contain less content. Second, within an ICO, connected reviewers write more positive reviews. Their narrative has a greater percentage of positive sentences and fewer percentage of negative sentences. The overall sentiment of their textual reviews is also more positive when they are connected.

Within experts, we find a similar pattern. When a reviewer rates an ICO where she has either a direct or indirect connection, she is more positive in her assessment of the offering. This analysis, therefore, documents that even a potential relationship with the current ICO team incentivizes reviewers to provide textual content that is more positive and potentially biased. Next, we examine whether investors can discriminate between ICOs that may have a higher number of experts that have potential conflicts of interest.

7.2 Can investors identify potential conflicts of interest?

In order to determine whether connected experts' potentially biased opinions are believed or discounted by investors in terms of the amount of proceeds raised, we categorize the average overall sentiment reviews according to how connected to the ICO the expert may be. For each ICO, we classify reviewers based on the magnitude of their indirect connection and then average the sentiment scores of the reviews in each classification. The classifications include 1) *Experts – High Indirect Connections*, the average sentiment scores of experts in the offering who are above the median indirect connection, 2) *Expert – Low Indirect Connections*, the average sentiment scores of experts in the offering who are below the median indirect connection, and 3) *Expert – No Connections*, the average sentiment scores of experts with no connection to team members of the ICO.

For the entire sample, there are 65 experts in the high indirect connection group who contribute 3107 textual reviews and 168 experts in the low indirect connection group who contribute to 3162 textual reviews. The 151 experts in the no connection group contribute 1661 textual reviews.

If conflicts of interest are ignored or unknown to investors, then we expect that reviews contributed by experts with high indirect connections will be related to the proceeds raised. If, on the other hand, investors are aware of conflicts of interest by carefully reading the reviews and doing due diligence on the expert, they will discount the information contained in the reviews of connected experts. If this is the case, then the effect of reviewer sentiment and proceeds raised will be primarily driven by the reviews of experts with low or no potential connections.

Table 11 presents the results of this analysis and as done previously, we control for the quality of the ICO by incorporating the platform's metrics. In columns (1) and (2), the sample includes only those ICOs with connected experts. The results show that proceeds raised is increasing in the sentiment of *less* connected experts and the coefficient on the sentiment of highly connected experts is insignificant.

We repeat this analysis in columns (3) and (4) but restrict the analysis to only those ICOs that also have experts with no connections. (This reduces the sample size somewhat.) Once all three types of reviewers are in the same specification, we find that proceeds are increasing in the positivity of the sentiment only for those reviewers with no connection to other ICOs.

Collectively, these sets of results imply that even in markets as unregulated as those of ICOs, investors are able to differentiate among reviewers who may be biased in providing a positive review because of their connections. One reason why investors may discriminate among reviewers is because the platform itself oversees both the expert's content and her potential for conflicts of interest. Moreover, ICObench provides transparency at the expert level, not only on her objective rating statistics, but also how well the reviewer meets the platform's specific criteria. Thus, self-oversight of information production by rating platforms, if done professionally, can mitigate to some degree conflicts of interest that may affect investor's decisions.

8. Discussion and conclusion

The growth of the ICO market highlights the interest of retail investors in participating in early stage financing of companies, investments in which they often do not have access. Recent regulatory initiatives such as the JOBS Act expands the retail investor base to private offerings such as crowdfunding but limits the amount of capital an investor can provide. The securities laws of private offerings, more generally, restrict either sales to specific investors or the amount a non-accredited investor can purchase, thus ICOs sought to bypass such restrictions by claiming that token sales were not securities. Whether or not all ICOs are securities, is an area that has yet been codified by rulemakers and therefore, this market is of interest to academics because it provides a natural platform to examine potential issues in the absence of regulation. The lessons learned from the experience of both companies and investors should be of interest to regulators as they continue to reform the regulations that create a public/private offering market divide.

The literature in general, and this paper in particular, highlights the potential for markets to self-regulate. Unregulated markets, such as those for token offerings, suffer from a lemons problem whereby investors are unable to differentiate good offerings from bad. Platforms, such as ICObench, attempt to replicate the services of other financial intermediaries in well-established offering markets such as underwriter and rating agencies to overcome information asymmetry. The platform helps entrepreneurs "list" and market offerings and provides some certification of the ICO's quality. It does so by providing not only its own assessment of the ICO, but also crowdsourcing opinions from experts. These experts, in turn, are monitored by the platform and their quality is also assessed. By doing so, these platforms are able to partially resolve the lemons problem.

Our results suggest that both the platform's assessment and the contribution of its reviewers predict outcomes. By allowing individuals to provide voluntary reviews with some constraints, the platform can leverage the ICO community without having to hire analysts. Reviewers are willing to provide these services for free in return for the potential for paid participation as a consultant or team member in future ICOs. Our results are consistent with reviewers being motivated to provide textual reviews in order to increase their reputation on the platform. As they gain experience and reputational capital, their reviews become more balanced over time. Furthermore, these reviewers provide a valuable service to the issuer. We document that the more positive the reviews and the higher consensus among reviewers are, the greater the amount of proceeds raised. Thus, expert textual content provides investors with information that may be used in an investment decision and may mitigate issues of information asymmetry.

The content of these reviews, however, are not without controversy. We show that experts with a higher probability of having a conflict of interest also produce reviews that are more positive, consistent with the notion that conflicted reviewers may hype an offering. On the positive side, however, investors seem to understand these conflicts of interest and discount the reviews of potentially conflicted reviewers. Thus, our results suggest that some but not all frictions in unregulated markets can be mitigated by the platform's transparency around reviewer characteristics and oversight of her ratings and reviews.

Thus, the lessons learned from this market may be applicable in formulating a policy/market approach to investor access to early stage companies. The challenge is to overcome the potential for the informed to prey on the uninformed while at the same time promoting capital formation. The current approach of limiting access or investment limits of unaccredited investors to most private offerings reduces the amount of capital available to smaller issuers. If the ICO market is any indication, there is an appetite among retail investors for these types of offerings. Fostering the creation and oversight of information intermediaries with reputational capital at stake, such as ICObench and others, may help overcome some of the adverse selection problems unsophisticated investors face in private markets.

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Table 1
Offering Characteristics

The table reports the number of observations, 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, and 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. *White Paper Link* is an indicator variable equal to one if th*Number of Team Members* is the number of team members reported by the issuer. *Number of Restricted Countries* is the number of countries in which the ICO cannot be sold.

	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	3357	57.46	36.00	64.91
White Paper Link	4345	0.96	1	0.2
Number of Team Members	4049	13.15	12	7.88
Number of Restricted Countries	4345	1.09	0	3.57

Table 2

Platform ICO Metrics

This table presents the number of observations (N), mean and median for each metric attribute. *Benchy Rating* is a rating assigned to an offering based on 20 criteria determined by the platform ICObench using an automated algorithm. The rating scale is 1-5 and summary statistics are only for the sample of ICOs with expert ratings. In addition, the platform discloses the number of team members that provided information to the platform *Number of Team KYC Successes* as well as providing an ICO Success Score (ISS) to each team member that is based on the team member's participation in past successful offerings. *Maximum* and *Minimum ISS Score of Team Members* is the maximum and minimum ISS score assigned to a team member.

	N	Mean	Median
Benchy Rating	2296	3.33	3.40
Number of KYC Team Successes	4345	0.54	0
Mean ISS Score of Team Members	2165	7.56	4.35
Median ISS Score of Team Members	2165	3.03	3.00
Maximum ISS Score of Team Members	2165	46.25	13.20
Minimum ISS Score of Team Members	2165	2.76	3.00

Table 3

Numerical Ratings Provided by Experts

Experts provide numerical scores and textual reviews for an offering on ICObench. 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			
Rating-Team	2296	3.42	3.8
Rating-Vision	2296	3.45	3.7
Rating-Product	2296	3.18	3.4

Table 4
Textual Reviews by Experts

Experts provide numerical scores and textual commentary for an offering. Panel A reports the mean, median, and standard deviation of *Number of Experts, Number of Words in All Reviews, Number of Sentences in All Reviews, Sentiment-Al, % Positive, % Negative, % Neutral Sentences*, and the *Number of Agrees* at the review level. The sentiment categorization of each sentence and the overall sentiment of the review is obtained by using the Stanford Natural Language Processing (SNLP) sentiment engine. Panel B reports the same variables but at the offering level. In Panel C, the sample of offerings is split by groups based on number of experts covering an offering.

Panel A: Review Level Information (N=7930)

	Mean	Median	Std Dev
Number of Words per Review	70.85	45.00	118.06
Number of Sentences per Review	4.39	3.00	5.51
Sentiment-All	3.32	3.28	0.52
% Positive Sentences	46.33	50.00	35.29
% Negative Sentences	23.18	14.29	28.32
% Neutral Sentences	30.50	28.57	29.47
Number of Agrees	2.53	1.00	4.87

Panel B: Offering Level Review Information (N=1578)

	Mean	Median	Std Dev
Number of Reviewers	5.03	3.00	6.68
Number of Words in All Reviews	356.04	146.50	549.06
Number of Sentences in All Reviews	22.04	10.00	32.11
Sentiment-All	3.13	3.14	0.38
% Positive Sentences	38.96	37.31	25.29
% Negative Sentences	28.16	25.11	22.18
% Neutral Sentences	32.89	33.33	20.82

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

	All	1	2–3	4–10	> 10
Number of ICOs	1,578	544	406	433	195
Median Funds Raised ($ mill)	5.02	6.70	7.00	6.96	6.63
Mean Number of Words in All Reviews	356.04	77.81	171.15	431.53	1349.59
Mean Number of Sentences in All Reviews	22.04	4.70	10.57	26.67	84.04
Sentiment-All	3.13	3.08	3.15	3.15	3.21
% Positive Sentences	38.96	37.96	39.13	38.71	41.92
% Negative Sentences	28.16	30.67	27.54	26.85	25.32
% Neutral Sentences	32.89	31.37	33.34	34.44	32.76

Table 5

Determinants of Expert Coverage

This table shows the relation between expert coverage and ICO attributes. The dependent variable *Expert Coverage* is an indicator variable equal to one if an expert provides a numerical ranking (column 1) or a textual review (column 3) for an ICO, otherwise it is zero. The second dependent variable is *Ln(Number of Experts)* that provides a numerical ranking (column 2) or a textual review (column 4) for an ICO. ICObench metrics includes the algorithmic *Benchy Rating*, the median ICO Success Score (ISS) of team members that is based on the team member's participation in past successful ICOs, and *Number of KYC Team Successes*, the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. *White Paper* is an indicator variable equal to one if the issuer provides a link to a white paper, zero otherwise. *Number of Team Members* is the number of team members reported by the ICO issuer. *KYC Registration* equals one if the buyer/investor provides registration information. *Whitelist Registration* 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 the algorithmic rating provided by ICObench. *Number of Restricted Countries* is the number of countries in which the ICO cannot be sold. We include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin. These offering-related variables are described in detail in Appendix 5 and 6.

	Numerical Ratings		**Textual Reviews**	
	Expert Coverage (1)	Ln(Number of Experts) (2)	Expert Coverage (3)	Ln(Number of Experts) (4)
Benchy Rating	0.380***	0.319***	0.424***	0.348***
	(4.17)	(6.58)	(4.33)	(6.68)
Median ISS Score of Team Members	-0.027	0.016**	0.002	0.003
	(-1.54)	(2.04)	(0.09)	(0.38)
Number of KYC Team Successes	0.491***	0.157***	0.601***	0.186***
	(8.15)	(5.27)	(9.98)	(6.36)
White Paper	-0.377	-0.329**	-0.176	-0.440**
	(-1.61)	(-2.52)	(-0.59)	(-2.35)
Number of Team Members	0.037***	0.019***	0.039***	0.018***
	(6.66)	(6.19)	(6.83)	(5.81)
KYC Registration	-0.344***	-0.257***	0.090	-0.138**
	(-3.56)	(-4.42)	(0.89)	(-2.42)
Whitelist Registration	0.042	0.046	0.294***	0.048
	(0.44)	(0.84)	(3.00)	(0.90)
Number of Restricted Countries	0.011	-0.012**	0.021**	-0.007
	(1.06)	(-2.43)	(1.98)	(-1.54)
Constant	-2.387***	-0.397**	-3.824***	-0.146
	(-8.09)	(-2.34)	(-9.85)	(-0.60)
Token Platform FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Social Media FE	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	4049	2004	4049	1517
Pseudo/Adjusted R-squared	0.171	0.266	0.247	0.283

Table 6

Factors Impacting the Probability of a Subsequent Textual Review

The table shows the relation between subsequent reviews and prior experience and community feedback. The dependent variable takes the value of 1 if the expert provides at least one textual review on day t+1 when s/he provides a numerical rating, and 0 if the expert provides a numerical rating but does not provide a textual review. *Experience* is defined as the logarithm of the cumulative number of offerings reviewed until day t. *Positive Feedback* is defined as the logarithm of 1 plus the cumulative number of "agrees" on an expert's textual reviews until day t. ICObench metrics includes the algorithmic *Benchy Rating*, the median ICO Success Score (ISS) of team members that is based on the team member's participation in past successful ICOs, and *Number of KYC Team Successes*, the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. Other control variables included but not shown to conserve space include: *Number of Team Members, KYC Registration, Whitelist Registration, White Paper*, and *Number of Restricted Countries*. We include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin. The observation level is review-day.

	Subsequent textual review at t+1 conditional on a numerical rating (1)	Subsequent textual review at t+1 conditional on a numerical rating (2)	Subsequent textual review at t+1 conditional on a numerical rating (3)
Experience	0.062***		0.056***
	(3.15)		(3.38)
Positive Feedback		0.098***	0.095***
		(6.75)	(6.67)
Benchy Rating	0.024*	0.035***	0.021
	(1.80)	(2.72)	(1.60)
Median ISS Score of Team Members	0.002	0.002	0.002
	(0.61)	(0.66)	(0.73)
Number of KYC Team Successes	0.029***	0.034***	0.026***
	(3.14)	(3.25)	(3.01)
Constant	0.549***	0.679***	0.509***
	(5.73)	(7.95)	(5.42)
Expert FE	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Token Platform FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Social Media FE	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	5222	5222	5222
Adjusted R-squared	0.339	0.352	0.361

Table 7

Determinants of the Content of Expert Textual Reviews

The table presents the results of analysis on the determinants of the content of expert textual reviews. The dependent variables represent the content of the textual reviews and are as follows: the number of words in the entire review, the percentage of sentences in the review that are positive, the percentage of sentences that are negative, the percentage of sentences that are neutral, and the overall sentiment score of the review. The sentiment categorization of each sentence and the overall sentiment of the review is obtained by using the Stanford Natural Language Processing (SNLP) sentiment engine. *Experience* is defined as the logarithm of the cumulative number of offerings reviewed until day t. *Positive Feedback* is defined as the logarithm of 1 plus the cumulative number of "agrees" on an expert's textual reviews until day t. ICObench metrics includes the algorithmic *Benchy Rating*, the median ICO Success Score (ISS) of team members that is based on the team member's participation in past successful ICOs, and *Number of KYC Team Successes*, the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. Other control variables included but not shown to conserve space include: *Number of Team Members, KYC Registration, Whitelist Registration, White Paper*, and *Number of Restricted Countries*. We include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin. The observation level is review-day.

	Number of Words	% Positive Sentences	% Negative Sentences	% Neutral Sentences	Sentiment-All
	(1)	(2)	(3)	(4)	(5)
Experience	10.070*	-0.034***	0.023***	0.011*	-0.042***
	(1.66)	(-3.73)	(3.40)	(1.85)	(-3.52)
Positive Feedback	-0.641	-0.013	0.015**	-0.002	-0.009
	(-0.17)	(-1.57)	(2.58)	(-0.25)	(-0.80)
Benchy Rating	8.212	0.039***	-0.023**	-0.016	0.053***
	(1.50)	(2.80)	(-2.30)	(-1.37)	(2.91)
Median ISS Score of Team Members	-0.982	0.003	-0.007***	0.004	0.008*
	(-1.48)	(0.70)	(-2.84)	(1.11)	(1.78)
Number of KYC Team Successes	3.830	0.010	-0.005	-0.005	0.013
	(1.25)	(1.24)	(-0.70)	(-0.75)	(1.16)
Constant	-57.522*	0.383***	0.324***	0.292***	2.047***
	(-1.70)	(4.94)	(4.47)	(3.46)	(16.44)
Expert FE	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Token Platform FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Social Media FE	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	4079	4079	4079	4079	4079
Adjusted R-squared	0.427	0.197	0.191	0.099	0.196

Table 8

Funds Raised and the Sentiment of Expert Textual Reviews

The table reports the relation between sentiment of expert textual 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, Sentiment-Vision* and *Sentiment-Product* are generated by the Stanford Natural Language Processing (SNLP) sentiment measure based on the textual reviews. *Sentiment-All* is generated based on all the sentences in the textual review. *Sentiment-Team* is based only on the sentences related to team. *Sentiment-Vision* is based only on the sentences related to vision. *Sentiment-Product* is based only the sentences related to the product. *Rating-Team, Rating-Vision*, and *Rating-Product* are the numerical ratings of the reviewer. ICObench metrics includes the algorithmic *Benchy Rating*, the median ICO Success Score (ISS) of team members that is based on the team member's participation in past successful ICOs, and *Number of KYC Team Successes*, the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. All variables have been standardized for ease of interpretation. Other control variables included but not shown to conserve space include: *Number of Team Members, KYC Registration, Whitelist Registration, White Paper*, and *Number of Restricted Countries*. We include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin. The observation level is ICO.

	Proceeds Raised			
	(1)	(2)	(3)	(4)
Sentiment-All	0.218***			
	(3.28)			
Sentiment-Team		0.220***		
		(3.16)		
Sentiment-Vision			0.184***	
			(2.91)	
Sentiment-Product				0.263***
				(4.17)
Rating-Team		0.351**		
		(2.01)		
Rating-Vision			0.378**	
			(2.28)	
Rating-Product				0.310**
				(2.07)
Benchy Rating	0.406***	0.343***	0.342***	0.316**
	(3.24)	(2.71)	(2.70)	(2.52)
Median ISS Score of Team Members	0.093***	0.083***	0.082***	0.084***
	(3.35)	(3.06)	(3.08)	(3.18)
Number of KYC Team Successes	-0.329***	-0.330***	-0.306***	-0.329***
	(-4.29)	(-4.27)	(-4.00)	(-4.26)
Number of Team Members	0.028***	0.024***	0.026***	0.024***
	(4.05)	(3.38)	(3.70)	(3.56)
Constant	13.988***	13.839***	13.503***	13.628***
	(12.48)	(12.31)	(11.81)	(12.22)
Control Variables	Yes	Yes	Yes	Yes
Token Platform FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Social Media FE	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	733	733	733	733
Adjusted R-squared	0.137	0.147	0.143	0.152

Table 9

Consensus and Proceeds Raised

The table reports the relation between expert consensus 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 *Consensus-Textual* is the average pairwise cosine similarity of the content all textual reviews for an ICO. *Rating-Team, Rating-Vision*, and *Rating-Product* are the numerical ratings of the reviewer. *Consensus-Rating-Team, Consensus-Rating-Vision*, and *Consensus-Rating-Product* are the standard deviation of the numerical ratings of the reviewer for each of the three categories multiplied by -1. ICObench metrics includes the algorithmic *Benchy Rating*, the median ICO Success Score (ISS) of team members that is based on the team member's participation in past successful ICOs, and *Number of KYC Team Successes*, the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. All variables have been standardized for ease of interpretation. Other control variables included but not shown to conserve space include: *Number of Team Members, KYC Registration, Whitelist Registration, White Paper*, and *Number of Restricted Countries.* We include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin. The observation level is ICO.

	Proceeds Raised		
	(1)	(2)	(3)
Consensus-Textual	0.240**	0.256**	0.226*
	(2.12)	(2.19)	(1.96)
Rating-Team	0.298**		
	(2.28)		
Rating-Vision		0.303**	
		(2.22)	
Rating-Product			0.262**
			(2.34)
Consensus-Rating-Team	-0.068		
	(-0.57)		
Consensus-Rating-Product		-0.113	
		(-1.05)	
Consensus-Rating-Vision			0.183*
			(1.85)
Benchy Rating	0.231	0.238	0.231
	(1.36)	(1.41)	(1.35)
Median ISS Score of Team Members	0.099**	0.098**	0.091**
	(2.18)	(2.15)	(2.00)
Number of KYC Team Successes	-0.373***	-0.362***	-0.384***
	(-3.91)	(-3.83)	(-4.05)
Number of Team Members	0.015	0.018**	0.016*
	(1.59)	(1.98)	(1.77)
Constant	15.291***	15.133***	14.909***
	(15.06)	(14.86)	(14.79)
Control variables	Yes	Yes	Yes
Token Platform FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Social Media FE	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	409	409	409
Adjusted R-squared	0.142	0.143	0.157

Table 10

Conflict of Interest and the Sentiment of Expert Textual Reviews

The table presents the results of analysis on the determinants of the sentiment of expert textual reviews. The dependent variables represent the content of the textual reviews and are as follows: columns (1) and (5) the number of words in the entire review, columns (2) and (6) the percentage of sentences in the review that are positive, columns (3) and (7) the percentage of sentences that are negative, columns (4) and (8) the percentage of sentences that are neutral, and columns (5) and (10) the overall sentiment score of the review. The sentiment categorization of each sentence and the overall sentiment of the review is obtained by using the Stanford Natural Language Processing (SNLP) sentiment engine. In Panel A, *Direct Connection* is an indicator variable equal to one if the expert has been on the same team as any member of the ICO's team in the past, zero otherwise. In Panel B, *Indirect Connections* is defined as the number of ICO team members that an expert has worked with in other ICOs over the entire sample. ICObench metrics includes the algorithmic *Benchy Rating*, the median ICO Success Score (ISS) of team members that is based on the team member's participation in past successful ICOs, and *Number of KYC Team Successes*, the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. Other control variables included but not shown to conserve space include: *Number of Team Members, KYC Registration, Whitelist Registration, White Paper*, and *Number of Restricted Countries*. We include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin. The observation level is review.

	Number of Words (1)	%Positive Sentences (2)	%Negative Sentences (3)	%Neutral Sentences (4)	Sentiment All (5)	Number of Words (6)	%Positive Sentences (7)	%Negative Sentences (8)	%Neutral Sentences (9)	Sentiment All (10)
Panel A: Direct Connection										
Direct Connection	-25.787***	0.110***	-0.087***	-0.022	0.192***	-3.435	0.052***	-0.041***	-0.010	0.083***
	(-5.33)	(5.37)	(-6.90)	(-1.44)	(5.59)	(-1.48)	(3.07)	(-3.78)	(-0.81)	(3.50)
Benchy Rating						5.190**	0.042***	-0.021***	-0.021***	0.056***
						(2.02)	(4.26)	(-2.94)	(-2.63)	(4.04)
Median ISS Score						-0.289	0.007**	-0.005**	-0.002	0.010***
						(-0.79)	(2.55)	(-2.25)	(-1.04)	(3.16)
Number of KYC Team Successes						3.619**	0.005	-0.003	-0.002	0.009
						(2.13)	(0.98)	(-0.79)	(-0.42)	(1.22)
Constant	73.814***	0.460***	0.234***	0.306***	2.313***	-0.169	0.209***	0.490***	0.301***	1.876***
	(14.44)	(37.44)	(22.32)	(41.89)	(118.01)	(-0.01)	(2.98)	(6.52)	(5.36)	(12.38)
Control Variables	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
ICO FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Expert FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Token Platform FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Social Media FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Currency FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	7221	7221	7221	7221	7221	7221	7221	7221	7221	7221
Adjusted R-squared	0.035	0.106	0.107	0.022	0.132	0.416	0.181	0.179	0.072	0.221

Table 10 Continued

	Number of Words (1)	%Positive Sentences (2)	%Negative Sentences (3)	%Neutral Sentences (4)	Sentiment All (5)	Number of Words (6)	%Positive Sentences (7)	%Negative Sentences (8)	%Neutral Sentences (9)	Sentiment All (10)
Panel B: Indirect Connections										
Indirect Connections	-9.805***	0.030***	-0.018**	-0.013*	0.048***	-10.813***	0.032***	-0.021**	-0.011*	0.052***
	(-3.94)	(2.94)	(-2.40)	(-1.96)	(2.91)	(-4.05)	(2.74)	(-2.51)	(-1.71)	(2.82)
Benchy Rating						-1.996	0.016	-0.007	-0.009	0.026
						(-0.35)	(1.23)	(-0.71)	(-0.99)	(1.36)
Median ISS Score						-0.406	0.008***	-0.006**	-0.002	0.012***
						(-0.62)	(2.61)	(-2.39)	(-1.01)	(3.08)
Number of KYC Team Successes						5.479***	0.003	-0.002	-0.001	0.003
						(2.80)	(0.30)	(-0.30)	(-0.14)	(0.27)
Constant	113.728***	0.333***	0.300***	0.367***	2.120***	91.705***	0.046	0.643***	0.311***	1.582***
	(7.72)	(7.33)	(9.75)	(12.05)	(30.33)	(4.51)	(0.66)	(8.17)	(4.71)	(12.12)
Control Variables	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
ICO FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Token Platform FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Social Media FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Currency FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	5894	5894	5894	5894	5894	5894	5894	5894	5894	5894
Adjusted R-squared	0.050	0.115	0.118	0.026	0.141	0.023	0.035	0.034	0.004	0.043

Table 11

Connected Experts and Funds Raised

The table reports the relation between expert reviews and funds raised in an offering. The dependent variable is the logarithm of the funds raised in an offering. The main independent variables of interest are: *Expert – High Indirect Connections* is the average sentiment scores of experts in the offering who are above the median indirect connections, *Expert – Low Indirect Connections* is the average sentiment scores of experts in the offering who are below the median indirect connections, and *Expert – No Connections* is the average sentiment scores of experts in the offering with no connections to the ICO team whatsoever. *Indirect Connections* is defined as the number of ICO team members that an expert has worked with in other ICOs over the entire sample.CObench metrics includes the algorithmic *Benchy Rating*, the median ICO Success Score (ISS) of team members that is based on the team member's participation in past successful ICOs, and *Number of KYC Team Successes*, the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. Other control variables included but not shown to conserve space include: *Number of Team Members, KYC Registration, Whitelist Registration, White Paper*, and *Number of Restricted Countries*. We include fixed effects for the token platform, industry, the presence of social media links, currency accepted, and country of origin. The observation level is at the ICO.

	Proceeds Raised			
	(1)	(2)	(3)	(4)
Expert-High Indirect Connections	-0.000	-0.027	-0.033	-0.040
	(-0.00)	(-0.35)	(-0.38)	(-0.46)
Expert-Low Indirect Connections	0.216**	0.229***	0.075	0.090
	(2.45)	(2.62)	(0.77)	(0.92)
Expert-No Connections			0.294***	0.272***
			(3.69)	(3.40)
Benchy Rating		0.608***		0.369*
		(3.32)		(1.68)
Median ISS Score of Team Members	0.078**	0.063**	0.084**	0.073*
	(2.42)	(2.09)	(2.21)	(1.95)
Number of KYC Team Successes	-0.215***	-0.389***	-0.264***	-0.368***
	(-2.78)	(-4.40)	(-2.75)	(-3.32)
Constant	15.275***	14.472***	15.989***	15.491***
	(20.68)	(17.34)	(15.41)	(13.23)
Control Variables	Yes	Yes	Yes	Yes
Token Platform FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Social Media FE	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	466	466	355	355
Adjusted R-squared	0.123	0.146	0.117	0.124

Table A.1

Variable Definitions

Name	Definition
ICO level variables	
Funds Raised	The amount of funds raised in the offering in million USD
Log(Funds Raised)	The logarithm of the Funds Raised
Expert Coverage for textual reviews	An indicator variable that equals one if at least one expert provides a textual review on the ICO, and zero otherwise
Ln(Number of Experts) for textual reviews	The logarithm of the number of experts who provide a textual review on the ICO
Expert Coverage for numerical rating	An indicator variable that equals one if at least one expert provides a numerical rating on the ICO, and zero otherwise
Ln(Number of Experts) for numerical rating	The logarithm of the number of experts who provide a numerical rating on the ICO
Sentiment-All	The overall sentiment score based on all the sentences in the textual reviews on an ICO. The sentiment for individual sentences is generated by the Stanford Natural Language Processing (SNLP) sentiment analysis engine.
Sentiment-Team	The sentiment score based on all the sentences related to team in the textual reviews on an ICO. The sentiment for individual sentences is generated by the SNLP sentiment analysis engine.
Sentiment-Vision	The sentiment score based on all the sentences related to vision in the textual reviews on an ICO. The sentiment for individual sentences is generated by the SNLP sentiment analysis engine.
Sentiment-Product	The sentiment score based on all the sentences related to product in the textual reviews on an ICO. The sentiment for individual sentences is generated by the SNLP sentiment analysis engine.
Consensus-Textual	The average of the cosine similarities from all the pair-wise cosine similarities of all the textual reviews on an ICO. This measure requires at least two textual reviews on an ICO.
Expert High Indirect Connections	The average sentiment score of experts in an ICO who are above the median connections
Expert Low Indirect Connections	The average sentiment score of experts in an ICO who are below the median connections
Expert No Connections	The average sentiment score of experts in an ICO who have no connections
Rating-Team	A numerical rating of 1-5 on ICO team contributed by experts. This is based on team 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	A numerical rating of 1-5 on ICO vision contributed by experts. This is based on the vision of the project.
Rating-Product	A numerical rating of 1-5 on ICO product contributed by experts. This is based on whether the project is in working order or concept, technology behind the product, and strategy and growth options.

Table A.1 Continued

Name	Definition
ICO level variables	
Consensus-Rating-Team	The standard deviation of the numerical ratings of the team category in an ICO multiplied by -1
Consensus-Rating-Vision	The standard deviation of the numerical ratings of the vision category in an ICO multiplied by -1
Consensus-Rating-Product	The standard deviation of the numerical ratings of the product category in an ICO multiplied by -1
Benchy Rating	A numerical rating of 1-5 assigned to an ICO based on 20 criteria determined by the platform ICObench using an automated algorithm
Number of Team Members	The number of team members reported by the issuer
Maximum ISS Score of Team Members	The maximum ISS score assigned to team members on the ICO team. ISS score is assigned by the ICObench platform as an ICO Success Score to each team member that is based on the team members participation in past successful offerings.
Minimum ISS Score of Team Members	The minimum ISS score assigned to team members on the ICO team.
Number of KYC Team Successes	The number of management team members that provide identify information to successfully pass the ICObench KYC requirement.
White Paper	An indicator variable equal to one if the issuer publishes a link to a white paper, zero otherwise
KYC Registration	An indicator variable that equals one if the buyer/investor provides KYC/AML registration information, and zero otherwise
Whitelist Registration	A indicator variable that takes the value of one if investors are required to register for the ICO in advance (less restrictive than KYC Registration), zero otherwise
Number on Restricted Countries	The number of countries where the tokens in the ICO cannot be sold
Soft Cap	The minimum amount of funds to be raised in million USD
Hard Cap	The maximum amount of funds to be raised in million USD
Duration of Offering	The number of days the offering was open
Token Platform FE	Indicator variables equal to one for each of the usage of Ethereum, Waves or Utility Token in an ICO, zero otherwise
Industry FE	Indicator variables equal if the ICO is in one of each of the following industry categories: Platform, Cryptocurrency, Business services, Investment, Software, Smart Contract, Internet, Entertainment, Infrastructure, Banking, Artificial Intelligence, Communication, Big Data, Media, Other, Retail, Health, Real estate, Education, Tourism, zero otherwise
Currency FE	Indicators variable equal to one for each of the currencies accepted in the ICO including US Dollar, Bitcoin, Litecoin, and Waves
Country FE	Indicators variable equal to one for each of the top 20 countries/regions where an ICO is issued including USA, Singapore, UK, Russia, Estonia, Switzerland, Hong Kong, Australia, Canada, Germany, Netherland, Cayman Islands, Malta, Gibraltar, British Virgin Islands, France, India, Japan, Slovenia UAE, zero otherwise
Social Media	Indicator variables equal to one if the issuer provides a link to each social media site: Telegram, Twitter, Youtube, Facebook, Bitcointalk, zero otherwise

Table A.1 Continued

Name	Definition
Review level variables	
Number of Words	The number of words in the textual review by an expert on an ICO
% Positive Sentences	The percentage of sentences that are classified as Positive or Very Positive by the Stanford Natural Language Processing (SNLP) sentiment analysis engine in the textual review by an expert on an ICO
% Negative Sentences	The percentage of sentences that are classified as Negative or Very Negative by the SNLP sentiment analysis engine in the textual review by an expert on an ICO
% Neutral Sentences	The percentage of sentences that are classified as Neutral by the SNLP sentiment analysis engine in the textual review by an expert on an ICO
Sentiment All	The overall sentiment score based on all the sentences in a textual review by an expert on an ICO. The sentiment for individual sentences is generated by the SNLP sentiment analysis engine.
Number of Sentences	The number of sentences in the textual review by an expert on an ICO
Number of Agrees	The number of agrees on the textual review by an expert on an ICO

Expert related variables	
Experience	The logarithm of the cumulative number of offerings reviewed by an expert until day t
Positive Feedback	The logarithm of 1 plus the cumulative number of agrees on an experts textual reviews until day t
Direct Connection	An indicator variable that equals to one if the expert has been on the same team as any member of the ICO's team prior to the ICO that the expert is reviewing, zero otherwise
Indirect Connections	The number of ICO team members that an expert has worked with in other ICOs over the entire sample

Table A.2

Summary Statistics of ICO Characteristics as Control Variables

The table reports the number of observations (N), mean, median and standard deviation for the characteristics of 4345 ICOs for the period January, 2015-September, 2018. 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 Team Successes is the number of management team members that provide identify information to successfully pass the ICObench KYC requirement. Whitelist Registration 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 ICOs 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
KYC Registration	4345	0.42	0	0.49
Whitelist Registration	4345	0.3	0	0.46
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				
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 A.3

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 A.4
Top-25 Most Active Experts

Reviewer	Numerical Ratings	Textual Reviews	Percentage Textual
Igor Karavaev	582	198	34.00%
Mofassair Hossain	471	233	49.50%
Nathan Christian	464	162	34.90%
Douglas Lyons	369	266	72.10%
Luca Cotta	357	122	34.20%
Vladimir Nikitin	311	56	18.00%
P.B. Stanton Esq.	252	104	41.30%
Hung Chih (Jason Hung)	230	148	64.30%
Nikolay Shkilev	225	89	39.60%
David Drake	222	62	27.90%
Amarpreet Singh	163	36	22.10%
Richard Kastelein	160	159	99.40%
Conston Taylor	159	147	92.50%
Nikolay Zvezdin	151	49	32.50%
Purushotham Maralappa	151	74	49.00%
Tyler Sanford	149	113	75.80%
Vlad Skakun	149	51	34.20%
Irina Nikitina	148	51	34.50%
James Sowers	147	59	40.10%
Berkay Alp	146	0	0.00%
Paul Mears	146	121	82.90%
Ian Scarffe	138	88	63.80%
Rick Tapia	135	79	58.50%
Simon Choi	129	0	0.00%
Vasily Sumanov	127	44	34.60%

Table A.5
Profile of a Top-25 Expert

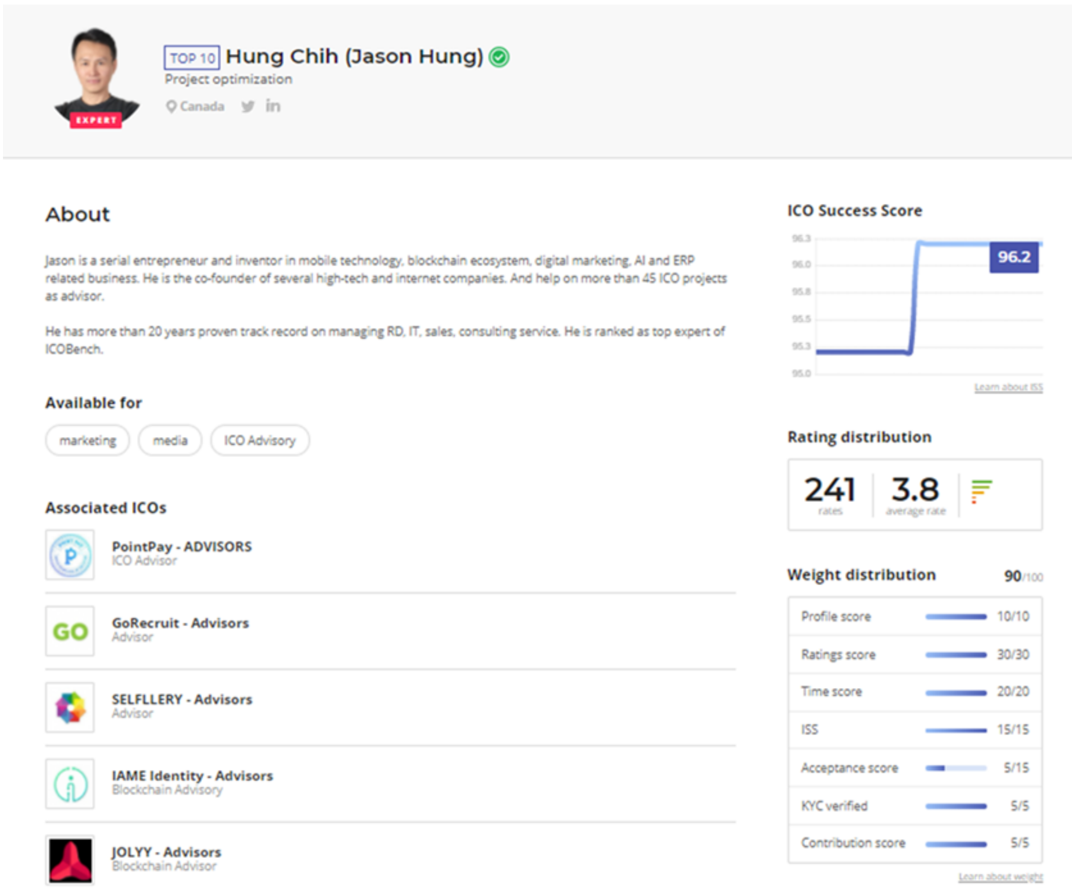


Table A.6

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

Bar Chart of the Topic Terms for the Five LDA Topics

Topic 1

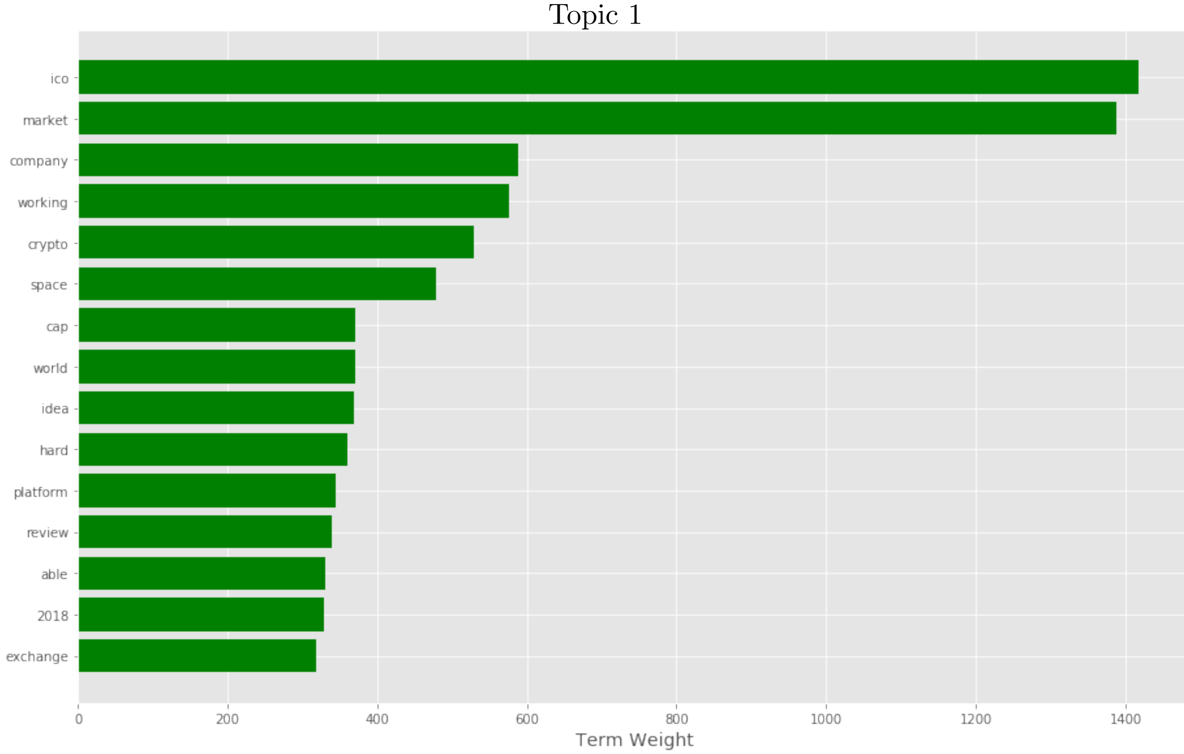
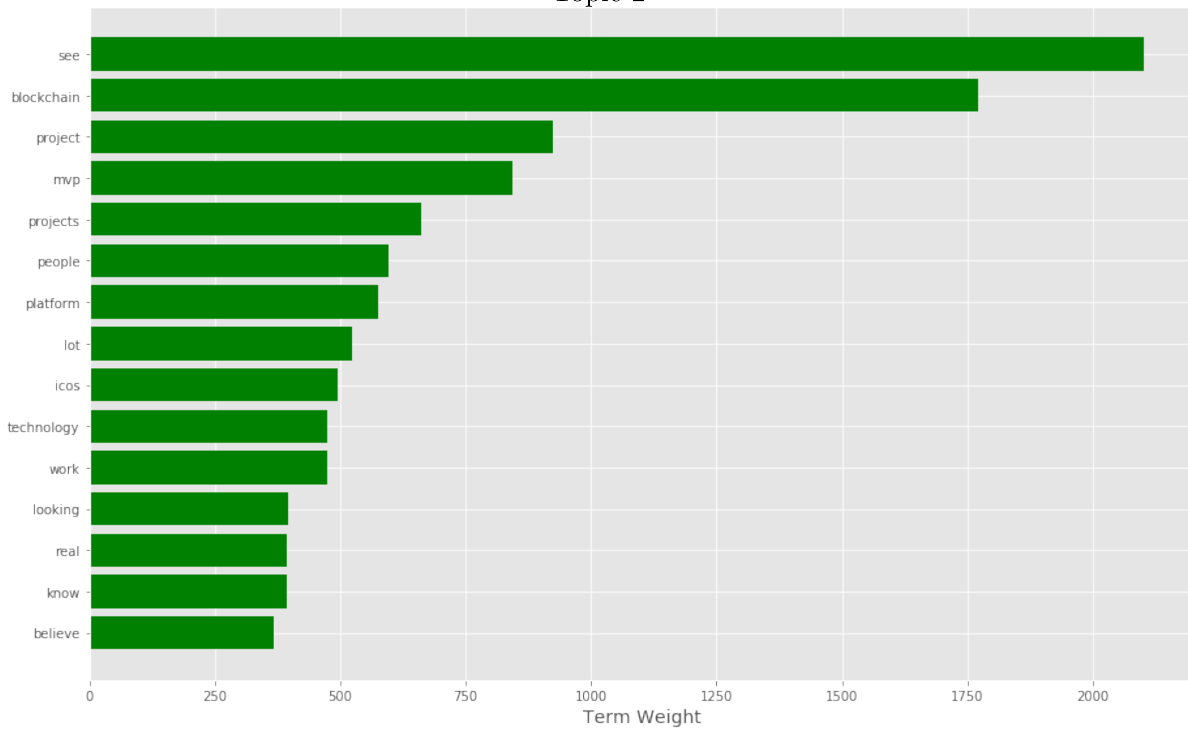


Table A.6 Continued

Topic 2



Topic 3

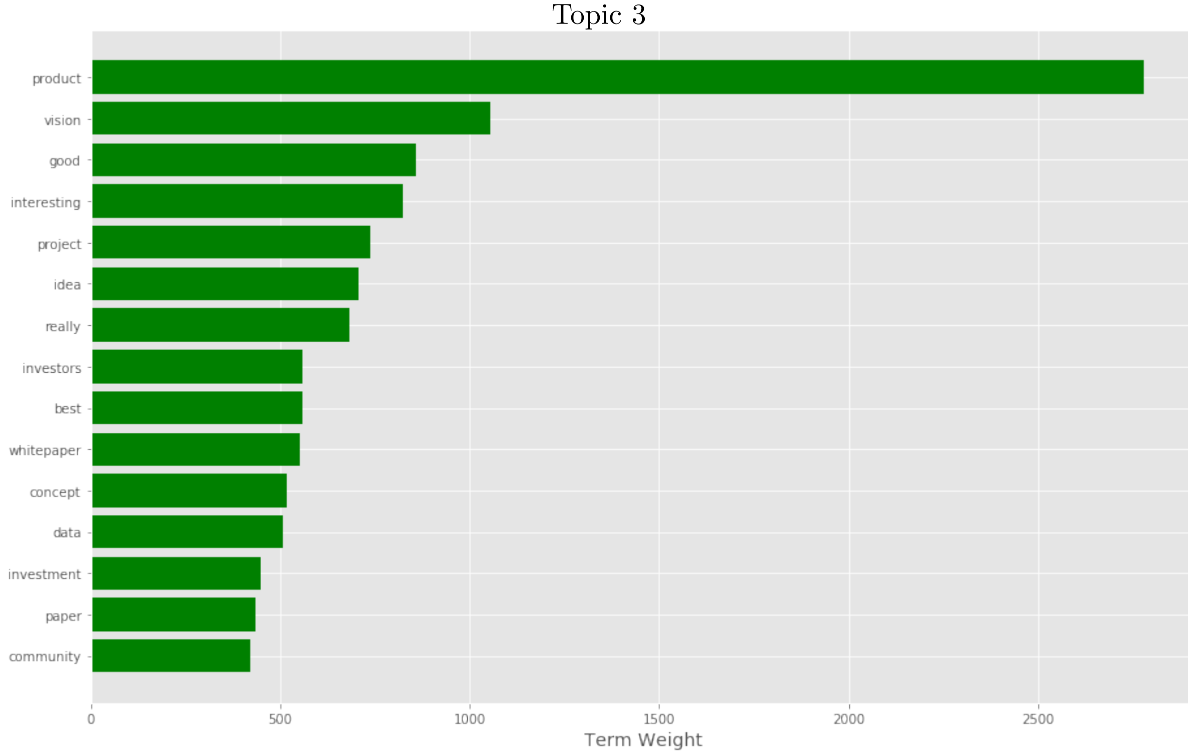
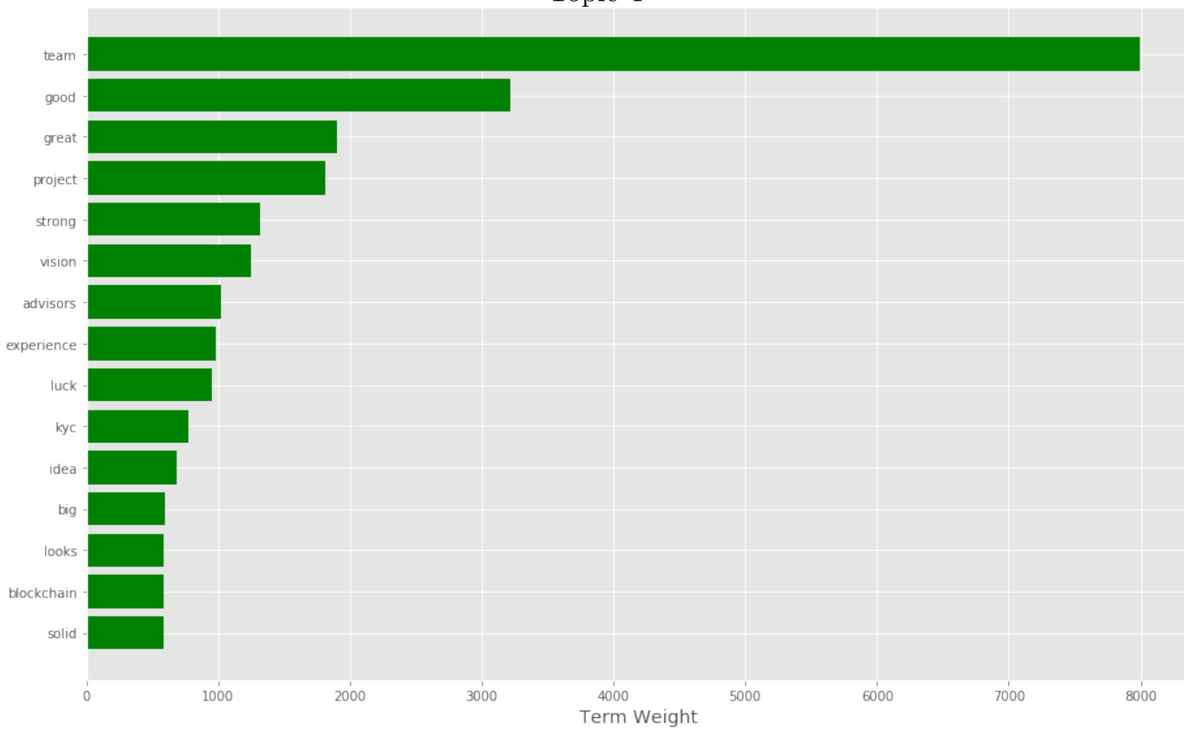


Table A.6 Continued

Topic 4



Topic 5

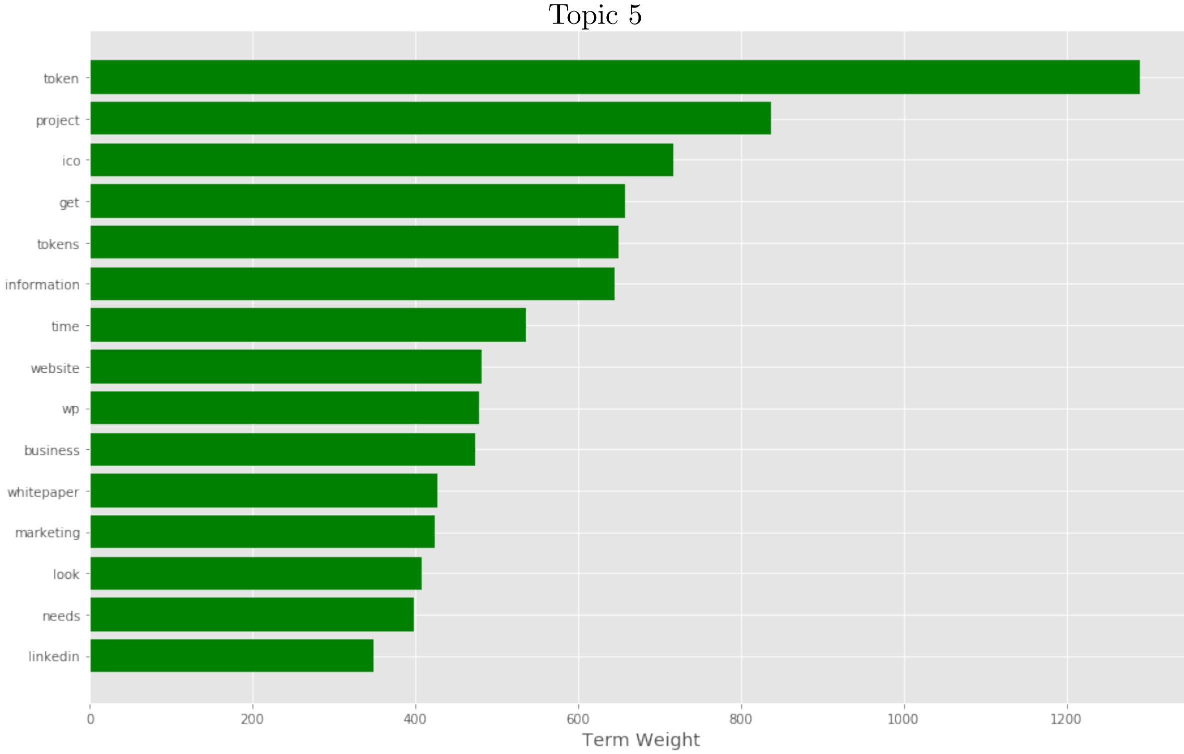


Table A.7

Examples of Review Sentences

This table presents examples of positive and negative sentiment words. The variables include the name of the ICO, the expert name, the experts numerical rating on product, vision, and team. The categorization of the sentences as positive or negative and the SNLP sentiment score.

ICO	Expert Name	Product Rating	Vision Rating	Team Rating	Category	SNLP Sentiment Score Review	SNLP Sentiment Score Sentence	Sentence
				Team				
Sharpay	Paul Mears	3	4	3	Positive	3.55	3.97	The team have impressed in being active, following up and open which is a good sign for ongoing success.
IGT	George Han	4	4	4	Positive	3.66	3.97	The team looks robust with relevant expertise in key areas of technology and business development.
ICOVO	Eleftherios Jerry Floros	5	5	5	Negative	3.66	2.51	The ICOVO team is a little bit thin and some expertise is missing.
IGT	Eleftherios Jerry Floros	4	5	4	Negative	3.44	2.46	With regards the team , there should be a bigger focus on experienced financial professionals such as COO , CFO and CCO (Chief Compliance officer) complementing the rest of the team , hence the 4 star rating for the team.
				Vision				
ImmVRse	Purushotham Maralappa	5	4	4	Positive	4.44	4.45	VR is the future video consumer and producer market, ImmVRse has good vision of connecting good VR producers and consumers with blockchain token model.
XAYA	Hung Chih (Jason Hung)	3	4	4	Positive	3.39	4.03	This project with very unique vision and the ability to execute.
BX.BET	Paul Cliffe	5	4	4	Negative	2.92	2.46	Vision - creating a trustless betting platform, not original but the market has many small players.
Dataeum	Chris Butler	4	4	4	Negative	3.09	2.46	Vision: This market is largely dominated by powerhouse companies like Google and Facebook.
				Product				
Bethereum	Giacomo Arcaro	5	3	4	Positive	4.06	4.26	Product is really well developed and explained properly on the whitepaper
AirPod	Tina Fotherby (Beaver)	5	4	4	Positive	3.21	3.97	This is clearly an innovative product with a vibration plate being used to enhance sound and video experiences.
BGX	Eugene Podkovyroff	3	4	3	Negative	2.62	2.57	Speaking of the BGX token as a product of the BGX ICO: it doesn't have any substantial calculation to support its tokenomics.
GigTricks	Douglas Lyons	1	1	4	Negative	2.46	2.46	This product is nothing more than a job board.

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