Confidence and Capital Raising

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Abstract
We investigate whether the confidence of management teams, defined as the certainty about handling what one desires to do, affects the capacity of firms to raise external capital. Drawing on psychology research, we run an experiment in which participants are asked to assess the confidence of the management teams of 515 initial coin offerings (ICOs) by appraising their pictures. Controlling for venture and offering characteristics, we find a positive association between confidence and the fundraising amount. The results are robust to alternative estimation methods and other visual traits such as attractiveness and intelligence. Our study highlights the importance of using images as a channel to communicate with prospective investors in alternative finance.

***JEL Classification*:** G32, M13, O16
Keywords: Capital raising, confidence, initial coin offerings, ICOs, alternative finance.

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1. Introduction

Corporate finance research has recently shown that the life experiences and psychological traits of managers are an important driver of success in organizations (e.g., Barnea et al., 2010; Bernile et al., 2017; Cronqvist et al., 2015; Malmendier and Nagel, 2011). Relatedly, a few studies have investigated the role of physical appearance in alternative finance. For instance, a positive association between appearance and the probability of receiving funding has been found in peer-to-peer lending (Duarte et al., 2012; Pope and Sydnor, 2011). The recent study by Momtaz (2019) investigates facial expressions in initial coin offerings (ICOs)[1] and reveals that CEOs showing fear or anger are associated with higher underpricing.

In this study, we investigate whether the confidence expressed by a management team affects its capacity to raise funds. It is indeed intriguing that finance studies have extensively focused on "overconfidence rather than just confidence" (Bai et al., 2019, p. 201).[2] Applied psychology defines confidence, using the constructs of hope (Snyder, 2000), self-efficacy (Bandura, 1997), optimism (Peterson, 2000), and resilience (Coutu, 2002), as "a personal certainty belief that one can handle what one desires to do or needs to be done" (Stajkovic, 2006, p. 1209). Having high confidence makes it more likely that people will initiate and sustain action. Higher levels of confidence are, in turn, connected to higher chances of successful performance (Locke and Latham, 2002). Since confidence is the "the antonym" of uncertainty (Stajkovic, 2006, p. 1208), it is meaningful to investigate its role in a market laden with uncertainty such as that of ICOs.

Confidence operates at the individual level of analysis, as it is based on individual appraisals rather than knowledge (Smith and Lazarus, 1993). Making an appraisal entails a

[1] An ICO is a decentralized method of financing, whereby a firm calls for funding by issuing coins to online investors. Coins (or tokens) are a digital medium of value exchange based on the blockchain, which can operate independently and be traded between investors.
[2] Bai et al. (2019) find that more confident money managers, conditional on performance, can secure more flows for their funds.

relative assessment of an aspect of a person in a context (Lazarus, 1991). In particular, neuroscience and psychology studies advocate that people quickly incorporate perceptions of facial cues into their subsequent decision-making (Borkenau et al., 2009; McClure et al., 2004; Todorov et al., 2010). More confident advisors (including financial advisors) are more likely to be considered by information receivers (Price and Stone, 2004; Sniezek and Von Swol, 2001). Supporting evidence is found in various areas such as housing markets (Burnside et al., 2016), e-commerce (Ahmad and Laroche, 2015), human resources management (Avey et al., 2011), leaders' and followers' psychological capital (Walumbwa et al., 2010), marketing selling (Larson et al., 2008), and political science (Tetlock, 2005). In this vein, we take the corporate finance perspective and argue that management teams that look more confident are more likely to be positively assessed by prospective investors and thus succeed in raising more funds.

Previous studies of investment criteria in early-stage finance have revealed the importance placed on the management team (the "jockey" in Kaplan et al., 2009) relative to the business model (the "horse") (e.g., Kaplan and Strömberg, 2004). Gompers et al. (2020) report that 95% of venture capitalists in their survey mention the management team as an important factor, 47% as the most important factor. The experiment by Bernstein et al. (2017) suggests that business angel investors are highly responsive to information about the founding team, whereas information about the traction and current investors does not increase interest. Adding to this discussion, we focus on the role of management teams in ICOs, where companies typically have a limited track record and the information available through external sources is scarce.

The number of ICOs and money raised through ICOs have increased considerably over recent years. A growing literature documents that the structure of the campaign, characteristics of the entrepreneurial team, and use of social media affect the capacity of firms to raise funds in ICOs (e.g., Blaseg, 2018; Chod and Lyandres, 2020; Roosenboom et al., 2020; Fisch, 2019;

Howell et al., 2019; Lyandres et al., 2020; Momtaz, 2020). A distinctive aspect of ICOs is that they occur only online, as ventures communicate with investors by providing information on the campaign site. We focus our attention on the visual information shared in ICO campaigns.

Images provide a straightforward way for the management teams of ICO ventures to share their self-presentation. Besides facial information, the profile pictures of ICO team members deliver behavioral cues such as expressions, poses, and clothes, which are the outcomes of their intentional choices, driven by psychological differences (Liu et al., 2016). Analyses of facial features, typically using pictures to identify and measure the perception of personal traits and behavioral cues, have been coherently used in psychology studies (Carré et al., 2009; Rule and Ambady, 2008; Wong et al., 2011) as well as in the economics (Hamermesh and Biddle, 1994; Mobius and Rosenblat, 2006), management (Addoum et al., 2017; Graham et al., 2016), and accounting literature (Blankespoor et al., 2017, Davison, 2010; He et al., 2019; Jia et al., 2014).

To empirically analyze the influence of team confidence on the fundraising amount, we run an experiment similar to that of Bai et al. (2019). Using the Amazon Mechanical Turk (mTurk) platform, we recruit 357 participants to assess the pictures of the management teams of 515 ICOs. A picture of an ICO venture team is presented to a participant, who is asked to make a judgment of how confident those people are as a team. Then, the participant selects a score on a five-point scale, where 5 stands for the highest ranking (most confident) and 1 for the lowest (least confident). Each team picture is evaluated by 10 participants. The sample of 515 ICOs is taken from Icobench from January 2017 to June 2018.

Controlling for other offering and venture characteristics, we find a positive relationship between perceived confidence and the amount of capital raised in ICOs. The results show that the relation between perceived team confidence and fundraising is not explained by other visual traits such as intelligence and attractiveness. Moreover, our results are robust to different estimation methods and the inclusion of additional control variables. This indicates that image plays a unique role as an information channel in fundraising.

The remainder of the paper proceeds as follows. In Section 2, we present the experiment, variables, and descriptive statistics. Section 3 discusses the empirical results and robustness tests. In Section 4, we provide concluding remarks.

2. Methods and context

2.1 The ICO context

ICOs are an appropriate testbed to investigate the role of confidence for three reasons that depend on the specific nature of the supply (i.e., issuing companies) and demand (i.e., digital investors) in this market as well as the object (i.e., tokens). First, ICOs are often used by early-stage start-up firms that have not yet developed products or services (Chen and Bellavitis, 2020). The traits of entrepreneurial teams are likely to matter in such a market where information asymmetries are endemic. Second, disintermediation brought about in entrepreneurial finance by digitalization brings new challenges, together with unprecedented opportunities, to investors. ICO investors operate under significant information constraints and, to succeed, must evaluate cues that indicate the magnitude of return expected for a potential investment. According to bounded rationality theories (Simon, 1979), agents might use heuristics[3] in these contexts to make investment decisions and economize on the acquisition of information using cues in the environment (Huang and Pearce, 2015). Third, ICOs are different than other types of entrepreneurial finance markets in that firms do not issue traditional securities but tokens. These are promised payment instruments to be redeemed for the products and services. However, investors have little certainty that the products and services will be

[3] Heuristics are mental shortcuts that individuals use to simplify decisions and can be implicit or explicit (Tversky and Kahneman, 1974).

developed and token price stability is also not guaranteed. If firms renege on their promise, investors have few options to file legal suits, as cryptocurrency tokens rarely fall under securities law; hence, no traditional investor protection laws apply (Howell et al., 2019). Thus, the confidence of management teams should affect the probability that the firm will deliver what was promised.

The ICO market itself is different than other entrepreneurial or corporate finance markets (Chod and Lyandres, 2020). It relies on blockchain technology to generate and develop business services and functions, which is a decentralized fundraising model, and thus provides better efficiency and lower transaction costs than traditional financial systems; coins/tokens are used as a medium to execute the proposed smart contract. Compared with other fundraising markets such as IPOs, peer-to-peer lending, and equity crowdfunding, an ICO—as blockchain-based decentralized finance—has limitations and challenges (Martino et al., 2019a, 2019b). Since the market and regulatory bodies are not yet mature, the ICO market is relatively vulnerable to scammers and frauds (Cumming et al., 2015). In the context of ICOs, it is possible to bypass country regulations and prospectus requirements that would normally apply to firms that seek to sell securities to the public (Bellavitis et al., 2020).

Our study also contributes to research on entrepreneurial finance, which has documented the importance of top management teams for early-stage ventures (e.g., Kaplan et al., 2009). This research has frequently identified the firm's CEO (and top management team) as one of or the most important criterion guiding investors' funding decisions. Physical and psychological attributes have only recently been addressed and not comprehensively linked to outcomes. Using a sample of ICOs, Colombo et al. (2020) document a positive relationship between CEO attractiveness and firm valuation. They document that investors do not mistake attractiveness for other latent traits, such as competence, intelligence, likeability, or trustworthiness. Rather, CEO attractiveness seems to bear economic value per se, as it helps attract institutional investors and has a sustainable effect on token price performance. A positive association between appearance and the probability of receiving funding has also been found in peer-to-peer lending (Duarte et al., 2012), which is a form of consumer finance where individuals borrow money from digital investors with the promise to return the capital (with interest) over a short time horizon. In such a setting, Ravina (2019) documents the impact of borrowers' personal characteristics such as beauty, race, and age on their likelihood of obtaining a loan.

2.2 The experiment

We use an online picture experiment on the mTurk platform to examine how people judge an ICO team based on its visual presentation (i.e., pictures of team members). Data on ICO ventures are obtained from the ICO listing website Icobench, which has frequently been used in previous ICO studies (e.g., Amsden and Schweizer, 2018; Fisch, 2019; Fisch et al., 2020; Huang et al., 2020; Lyandres et al., 2020) as well as white papers. We also cross-check our data with other sources such as Coinmarketcap and the ventures' websites. Given the availability of data for constructing our variables, the final sample of ICOs used in the experiment consists of 515 ICO campaigns between January 2017 and June 2018. In total, 357 participants from mTurk are asked to evaluate the given team pictures. Figure 1 displays six examples of ICO team pictures,[4] showing that different teams have various presentation styles. Figure 2 illustrates the experimental design, highlighting the instructions (Figure 2a) and experimental interface (Figure 2b).

[4] Face information is mosaicked here for illustration purposes owing to privacy concerns; however, clear pictures are used in the experiment.

Insert Figure 1 and Figure 2 About Here

2.3 Ecological validity and representativeness

To ensure the validity of the experiment, we first consider its procedural representativeness, that is, how closely the experiment reflects how potential investors evaluate an ICO in real life. As shown in Figure 1, for an ICO team, the team picture is generated by concatenating the pictures of the individual member profiles. The order of the individual pictures is in line with that presented by Icobench. We keep such a layout to maintain the original team presentation. It is important that participants are asked to evaluate an offering as they would encounter one in the real world to enhance the procedural representativeness of our experiment (Grégoire et al., 2019). Most ICO teams, for instance, present their CEO or founders first, followed general members.

Buhrmester et al.'s (2011) investigation demonstrates that mTurk participants are more representative than those of typical Internet and traditional samples. Recently, the mTurk platform has been widely used to recruit experimental participants in entrepreneurial finance research. For example, a number of studies (e.g., Chan et al., 2020; Mahmood et al., 2019) have used mTurk participants to study the content and judge the video pitches of crowdfunding projects. These works suggest that the mTurk platform is a valuable source of participants for studying crowdfunding phenomena. A similar argument applies to ICO investors. Moreover, younger people have a greater knowledge of advanced financial products than older people (e.g., Guiso and Jappelli, 2005) and are disproportionally more likely to use the Internet (van Dijk and Hacker, 2003).

Second, the experiment is robust from an internal validity perspective. In theory applications, a homogeneous group is preferred (Winer, 1999). Indeed, Lynch (1999) suggests that in experimental research, using a highly heterogeneous "representative" sample, across a wide age span, is likely inflated. For instance, while including older investors would increase the generalizability of our findings, differences in background factors would be ignored (e.g., the variance in income for older investors is higher and difficult to measure).

Lastly, in line with the guidelines for entrepreneurship research (Grégoire et al., 2019), we perform a pilot test with two academic colleagues before the actual experiment to enhance experimental realism and check for the absence of procedural distractions or other issues. To guarantee the quality of the response data, we only recruit participants who have experience of more than 1,000 HITs[5] and an approval rate greater than 95%. Participants are restricted to being from ICO-active countries in which at least five ICOs are completed during our sample period (from January 2017 to June 2018). Each trait is assessed by a large number of mTurk participants to reduce bias.[6] In total, 357 participants evaluate all the pictures. Panel A of Table 1 summarizes the details of the experiment.

No information about the ICO project is given in the experiment to ensure participants can make their judgment purely on the content of the pictures without bias, in line with an image perception experiment setting (Bai et al., 2019).[7] A picture of an ICO venture team is presented

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[5] HIT stands for "Human Intelligence Task," which is defined by the mTurk platform to refer to a task on which a participant can work and submit a response. The HIT approval rate is the rate that requesters (i.e., the people who set the experiment) have approved the HITs that participants complete. A requester can reject a HIT if the quality of the participant response (i.e., data) is low.

[6] We use the intra-class correlation coefficient (McGraw et al., 1996) to measure external consistency (i.e., mTurk respond consistency). A higher coefficient value indicates greater inter-rater reliability (consistency). The ICC value for our mTurk respond is 0.72, which indicates good consistency (Cicchetti, 1994).

[7] Fundamentally, we follow their concept to use image experiments to study people's perception of confidence. As we do not require the respondent to compare two people's confidence levels, there is no "pairwise" in our experiments. However, we try to generate two groups (high/low) based on the mean fundraising amount. We conduct the ANOVA test and find that, on average, the confidence score of high fundraising ICOs (*highfund*) is higher than that in the low fundraising group (*lowfund*) (i.e., Mean_highfund=0.206, Mean_lowfund=0.005, F=19.79, p<1.06e-05). In addition, following Bai et al. (2009), we generate 2,000 pairs of one randomly chosen high fundraising ICO and one low fundraising ICO (with pairwise matchups drawn without replacement). The percentage of high fundraising ICOs perceived as more confident is 61% (the significance level is p<2.2e-16 according to the two-tailed binomial test suggested by Bai et al. (2019)), which is much higher than a random guess (50%). Both tests show similar results to our baseline results in Table 4.

to one participant, who is asked to make a judgment of how confident those people are as a team. This procedure is in line with the finding by neuroscience and psychology studies that people rapidly develop perceptions of facial cues (Bar et al., 2006; Todorov et al., 2010). Our initial perceptions of others are formed in milliseconds (Todorov et al., 2015) and a longer exposure does not significantly change those first impressions (Willis and Todorov, 2006).

Each team picture is evaluated by 10 participants[8] and each participant is randomly shown 10 to 50 team pictures, one picture at a time. Each participant's scores are z-score-normalized to account for positivity or negativity bias. Finally, we calculate the average value of the 10 participants' responses as the visual confidence score of an ICO team (*Confidence*). This approach is applied to measure visual attractiveness (*Attractiveness*) and visual intelligence (*Intelligence*), which are discussed in Section 3.1. Panel B of Table 1 reports the correlation matrix of the three visual scores. While there are some moderate correlations because of the sample size, the variance inflation factors (VIFs) are below 10, indicating that multicollinearity should not be an issue in our estimations.

Insert Table 1 About Here

2.4 Regression model and variables

We perform a regression analysis to assess whether a significant relationship between perceived confidence and the capacity to raise funds exists. In line with previous studies (e.g., Fisch, 2019; Lyandres et al., 2020), the dependent variable is total capital raised in the ICO

[8] Using multiple raters is desirable to increase reliability (Hamermesh and Biddle, 1994; Mobius and Rosenblat, 2006). While a single-item measure might not fully capture the complex construct of confidence, the applied psychology literature typically uses this type of measure because perceptions are formed during the first few seconds of exposure and single-item measures capture spontaneous reactions better than longer scales (Langlois et al., 2000).

(*Amount raised*). We obtain funding data from Icobench. In the regressions, we use the natural logarithm of the amount of funding plus one (in USD). Specifically, we estimate the following ordinary least squares regression:

$$Amount\ raised_i = \alpha + \beta\ Confidence_i + \gamma\ ICO\ campaign\ characteristics_i + \varepsilon_i \quad (1)$$

where i represents each completed ICO published on Icobench (see Section 2.1) and *ICO campaign characteristics* are a vector of the control variables (defined below). The notation ε is a residual error term. Finally, we estimate our model using heteroscedasticity-robust standard errors and including individual fixed effects (i.e., the unique participant to the experiment is identified).

Below, we define each independent variable used in the analysis. Appendix A defines all variables used in our regressions.

Team size and *Team size squared*. A venture's team is important for attracting early-stage finance (Gompers et al., 2020; Kaplan and Strömberg, 2004; Kaplan et al., 2009). A relatively large team can signal management organization for conducting the ICO project and thus affect the investment decision and amount of funding. *Team size* is defined as the total number of management and advisory members, using information from Icobench and cross-checking with ICO venture websites and white papers. We also include the power of *Team size* (*Team size squared*) to control for the potential non-linearity in the relation between team size and confidence.

Member names. Investors tend to research each team member before making their financial decisions. Providing full names can help build trust between the ICO and potential investors. *Member names* is defined as the percentage of team members for which full names are available. We obtain this information from Icobench and also cross-check with the information from the venture's websites.

Pre-sale. Similar to the book-building process in initial public offerings, ICO ventures can use a pre-sale stage to determine demand and fix the offering price. Since pre-sales can exert a certification (Fisch, 2019; Howell et al., 2019), we include this as a control variable. *Pre-sale* is defined as a dummy variable coded one if there is a pre-sale in an ICO and zero otherwise. The data are available from Icobench.

Hardcap_ln. A hard cap indicates the maximum fundraising amount for the business, implying that the venture has estimated the amount of money required to execute the proposed project and business. *Hardcap_ln* is a natural logarithm of the hard cap of an ICO in US dollars. In line with Lyandres et al. (2020), we convert the amount of the hard cap in other currencies into US dollars using the exchange rate data listed on the last available day of the token currency website (Coinmarketcap).

Offered ownership. Retaining a large percentage of tokens, entrepreneurs signal their commitment to and engagement in the development of the firm (Leland and Pyle, 1977). This variable is defined as the percentage of tokens distributed in the ICO relative to all the tokens created (Fisch, 2019). We obtain the information on the offered token ownership from the ventures' white papers.

Offered tokens. Ventures can freely decide the number of tokens to be issued. A higher token number offered usually means a lower price for each token. Generally speaking, the number of tokens should not affect the amount of funds raised, since issuing trillions of tokens is not costly in ICOs. We define *Offered tokens* as the natural logarithm of the number of tokens issued by an ICO (Fisch, 2019). We obtain the number of offered tokens from Icobench and then cross-check the white papers.

Ethereum. While ICO teams can develop their own distributed ledger technology, this requires a complex capacity in programming and cryptography as well as significant resources. Alternatively, they can build on existing distributed ledger technologies such as Ethereum, which is a blockchain-based distributed computing platform. As Ethereum provides developers with the tools and standards (e.g., ERC20 protocol) to build blockchain applications easily, it has the potential to be established as the benchmark for ICOs. Creating an ICO on Ethereum means the new token has immediate interoperability with all the other tokens on the Ethereum blockchain, which may signal higher future utility for the new ICO. The variable *Ethereum* is a dummy variable coded one if the token is based on an Ethereum-based platform and zero otherwise (Fisch, 2019)[9]. The Ethereum-based information is obtained from Icobench.

Twitter. Reaching out to potential investors and maintaining open communication with them is important for an ICO campaign. Icobench monitors the activities of ICO ventures on different social networks such as Twitter to measure the degree of the ICO team's interaction with potential investors. Recent research (e.g., Smith et al., 2017) indicates that entrepreneurs increasingly manage business networks online, especially via Twitter. It is important for ICO ventures to be exposed to a wide range of networks to reach all types of investors. *Twitter* measures the activity level on Twitter and is obtained from Icobench at the beginning of each offering. This value is set in the range of [0, 1, 2, 3], where 0 means low activity and 3 means high activity. These data are from Icobench.

Female percentage. Gender difference is often considered in corporate finance studies (e.g. Fisch et al., 2020). We manually count the number of female members from each team picture and define *Female percentage* as the ratio of female members to the number of all members.

[9] ICO-firms can either develop their own distributed ledger technology or build on existing distributed ledger technologies. Coherent with the evidence from previous studies (e.g., Fisch, 2019), the most common standard to build on is Ethereum, used by 88% of the ICOs in our sample (Table 2). The second platform in our sample is WAVES, which is account for 11 out of 515 ICOs (2.1%). Other platforms, such as Hyperledger, NEO, or Azure, are used by less than 1% of the ICOs in our sample. There are also 16 ICOs that used their own platform. We checked the whole ICO listings on the Icobench website till March 2020 and confirmed that our sample is representative of the population. However, considering how dynamic the blockchain industry is, future studies should better investigate open source blockchains and related tools.

Location. The inclusion of *Location* is to examine the location effect (e.g., Stuart and Sorenson, 2003). Huang et al. (2020) show that ICOs take place more frequently in countries with developed financial systems, public equity markets, and advanced digital technologies. This is a dummy variable coded one if an ICO takes place in the top five countries sorted by the total fundraising amount in our sample (which are the United States, United Kingdom, Singapore, Russia, and Estonia) and zero otherwise. The ranking result is the same if we sort each country by their total number of ICOs. The data come from Icobench.

Trend effect. The trend variable is set to one for the first ICO in our sample set, two for the second ICO, and so on to the maximum level of 515 for the last ICO to occur in our sample period.

2.5 Descriptive statistics

Table 2 reports the summary statistics of the variables used in our regressions. On average, the amount raised is $8.04 million. Its descriptive statistics in the natural log form of the amount raised plus one are similar to those reported by Fisch (2019) in terms of the median and maximum values. We consider all the available campaigns including those with zeros to avoid sample selection bias, and the diversity of amount raised is greater in our sample than in Fisch (2019). The median number of team members is approximately 13 people. Consistent with Fisch (2019), the average *Offered ownership* is 58%, with min and max values of 1% and 100%. The average and median values of *Female percentage* are 0.13 and 0.12, indicating that the number of female members is relatively low in ICO firms. In our sample, 46% of ICOs take place in the top five countries of our ICO sample and 15% take place in the United States, sorted by the amount raised. The average campaign period is approximately 41 days, ranging between 26 days (1st quartile) and 55 days (3rd quartile), with 18 ICOs occurring within one day and one lasting for the maximum period (222 days). Surprisingly, not all ICOs provide white papers despite being an important mode of communicating with crowd investors. Altogether, 56% of ICOs in our sample provide valid white paper links. On the contrary, a blockchain white paper contains only the technical details of the distributed ledger technology and is not meant for marketing the project.

Insert Table 2 About Here

Table 3 presents the unconditional correlations between all the variables. The largest correlation with *Amount raised* is *Twitter* (r=0.35), indicating that the activity level on Twitter and fundraising activity have a positive relationship to some extent. Although some of the coefficients are moderately significant, the average VIF based on Model 4 in Table 4 is 2.10, which is below the classical threshold of 10 (or four for a relatively strict threshold), indicating a low chance of severe multicollinearity in our estimations.

Insert Table 3 About Here

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3. Results

Table 4 reports the results of estimating Eq. (1). Model 1 is estimated including participant fixed effects but no time fixed effects. Models 2 and 3 include year fixed effects and quarter fixed effects, respectively. Model 4 includes the variable *Trend effect* to control for the linear trend. In all four models, the coefficients of *Confidence* are positive and significant. Based on the confidence revealed in team images, some ventures raise more funds and others raise less. We find that a one standard deviation increase in the perceived confidence of the ICO team is associated with a 9.88% standard deviation increase in the fundraising amount. We use Model 4 as our baseline model in the following discussion.[10]

Insert Table 4 About Here

Among the control variables, *Team size* is positively and significantly associated with the amount raised. Fundraising for new or early-stage businesses is particularly challenging because of the limited business and financial information provided to investors. A larger team including advisory members can signal a higher capability of conducting the project. The coefficient of *Team size squared* is significant and negative, pointing to a U-shaped relation between team size and confidence.

In line with Fisch (2019), total ownership offered (*Offered ownership*) is insignificantly related to fundraising, while the number of tokens issued (*Offered tokens*) is a concern for investors. The crowd invests toward to a lower price and the fundraising amount is accordingly accumulated. Our results do not show that a pre-sale offer (*Pre-sale*) or hard cap information (*Hardcap_ln*) matter to the amount raised. In addition, the higher the activity level on Twitter (*Twitter*), the more funding is raised. *Female percentage* shows a negative association with the amount raised. This confirms previous results from the corporate finance literature as well as

[10] To simulate the original team presentation to survey respondents, we use a default gray profile picture provided by Icobench if one of the team member's pictures is missing. In our sample, we exclude an ICO venture if all team members' pictures are missing. Approximately 91.5% of the ICO ventures in our sample have pictures of all team members. However, we test whether our key findings are driven by the fact that some ventures have missing photos by excluding ventures with any missing photos of team members. The number of observations falls from 515 to 471. Untabulated results for these additional tests confirm the robustness of the key findings from Table 4 (and Table 5). Moreover, the estimates of these tests provide findings for the sample with observations having all team members' photos that are qualitatively similar to those reported in Tables 4 and 5.

recent results from the related crowdfunding literature (Cumming et al., 2019; Ewens and Townsend, 2020; Vismara et al., 2016).[11] The effect of *Location* is positive but insignificant.

3.1 Robustness analysis

3.1.1. Additional visual analysis

One potential concern about these results is that related traits other than confidence may also influence ICO fundraising via the confidence dimension indirectly. Some psychological traits may be overshadowed by an attractiveness halo whereby desirable attributions are preferentially ascribed to attractive pictures (Talamas et al., 2016). Similar to confidence, people want to project traits such as high attractiveness and intelligence to others in their profile presentations. Indeed, investors have been found to prefer new venture opportunities presented by attractive individuals over those pitched by less attractive individuals (Brooks et al., 2014). Moreover, both attractiveness and intelligence have been shown to be positively related to confidence (Judge et al., 2009). It is thus meaningful to evaluate whether *Attractiveness* and *Intelligence* can lead to similar results as *Confidence* for ICO fundraising.

In this section, we conduct further picture experiments as a robustness check to ensure that the team's confidence is derived from the "confidence" itself to some extent and does not stand for other similar traits. Participants are asked to make a judgment on the attractiveness and intelligence of a team based on the team image. The format of the attractiveness and intelligence experiments is identical to the confidence one, as shown in Figure 2; the only change is that we replace "confident/confidence" with "attractive/attractiveness" or "intelligent/intelligence" in line with the experimental setting of Bai et al. (2019).

[11] We cannot disentangle whether the motivations here result more from demand-side issues (i.e., entrepreneurs), pointing to gender differences in risk aversion and growth aspirations, or supply-side issues, pointing to investors' assumptions and stereotyping.

Table 5 reports the regression results when these two potential visual traits (*Attractiveness* and *Intelligence*) are controlled for (Models 1 and 2, respectively). We also include all three visual traits in one regression (Model 3). The results still show a positive coefficient of *Confidence*, which is consistent with our main finding. Since the mTurk experiment is based on only one team picture, it is difficult to eliminate all possible related character differences. These findings, however, suggest that the positive relation between *Confidence* and the amount raised is affected by team members' confidence itself rather than by similar traits such as attractiveness and intelligence. By additionally controlling for these similar traits, Model 3 in Table 5 shows that a one standard deviation increase in the perceived confidence of the ICO team is associated with an 8.35% standard deviation increase in the amount raised.

Insert Table 5 About Here

To examine what visual elements in a picture make a team look more confident, we conduct further analyses of the relationships between image elements and confidence. Based on the design of image coding in the literature (Liu et al., 2016; Segalin et al., 2016), we extract image elements at both the individual and team levels to capture the visual and semantic information in each team picture. Below, we explain the definitions and measurements of these elements.

Glasses percentage, *Suit percentage*, and *Smile percentage*. We manually count the number of members wearing glasses in a picture and calculate the percentage of members wearing glasses (*Glasses percentage*). We define the variables *Suit percentage* and *Smile percentage* similarly.

Crossed arms. Striking a professional pose such as crossing your arms is popularly suggested when taking a business profile picture (Lewis, 2012). We define a dummy variable

Crossed arms coded one if at least one member in the team picture has his/her arms crossed and zero otherwise.

Face proportion. The variable *Face proportion* is measured as the size of face areas in a picture. For a team picture, all face areas are first detected by a well-developed face detector provided by the machine learning platform Face++ (faceplusplus.com); then, we calculate the ratio between the size of face areas and size of the team image. A higher *Face proportion* suggests that members are closer to the camera.

Same place and *Same clothes*. We manually code a dummy variable *Same place* as one if at least two of the team member images are taken in the same place and zero otherwise. Team members with pictures taken in the same place are more likely to be physically connected than simply adding their images to listing websites or white papers to form a "virtual" team. Similarly, we also define *Same clothes* coded one if at least two team members are wearing the same team clothes and zero otherwise.

Uniform background. We manually code a dummy variable *Uniform background* as one if the background of the team picture is uniform (see Figures 1a, 1d, 1e, and 1f) and zero otherwise. A uniform background indicates that a team considers using the same presentation style.

Black and white image. We define a dummy variable *Black and white image* coded one if all members' images are non-color and zero otherwise. Some teams may convert members' photos into black-and-white images using image editing software to ensure a uniform style for the whole team. This also indicates that the team considers its presentation style and reflects the time and effort an ICO team devotes to communicating with potential investors, which is highly valued.

We run multiple linear regressions to test the relation between the visual elements and *Confidence* while controlling for *Team size*, *Team size squared, Female percentage,* and *Trend* *effect*. While we consider the female percentage among the regressors in the main analysis about capital raising, gender might also affect perceived confidence. Indeed, Seidman and Miller (2013) find that when browsing online, people pay more attention to the physical appearance of women than men. The facial cues of women might therefore be more relevant in the assessment.

Table 6 presents the results. For a better comparison, the results of the relations between the visual elements and *Attractiveness* and *Intelligence* as the dependent variables are also reported. Overall, when more people are wearing suits or smiling, investors receive a signal that this team is more confident. Using black-and-white images has a positive correlation with confidence as such images help create a uniform style for a team. Surprisingly, using a "crossed arms" pose, which is popular when taking business pictures, does not raise confidence. Finally, in our dataset, the aforementioned team-level visual elements (e.g., *Suit percentage*, *Smile percentage*, *Black and white image*) matter more than such individual-level elements.

In contrast to the results of *Confidence*, showing a "crossed arms" pose in a picture increases the attractiveness of a team, while wearing glasses does not. Taking a picture too close to the camera (*Face proportion*) decreases the attractiveness perception from images. As expected, wearing glasses and suits increases the perceived intelligence of a team. These observations confirm the findings of a study based on Facebook profile images (Wei and Stillwell, 2017). Moreover, applying a similar background presentation style (explained by *Same place*, *Uniform background*, and *Black and white image*) also helps increase the perception of intelligence.

Insert Table 6 About Here

To account for factors that may represent confidence perceived by people, beyond those visual elements captured in Model 1 of Table 6 for an individual's confidence perception, we conduct five additional tests to identify the unique effect of team confidence on ICO fundraising. First, in Model 1 of Table 7, we run an OLS regression with the residual estimated in Model 1 of Table 6 on the ICO amount raised. The result shows that other elements representing an individual's confidence not captured by the main visual elements such as wearing suits, smiling, and using a black and white image influence the amount raised in ICOs.

In Model 2 of Table 7, we re-run our baseline model (Model 4 of Table 4) including the three significant visual elements captured in Model 1 of Table 6 (i.e., *Suit percentage*, *Smile percentage,* and *Black and white image*). In Models 3 to 5 of Table 7, we re-run our baseline model (Model 4 of Table 4) by replacing *Confidence* with each of those three significant visual elements. As reported in Model 4 of Table 7, *Smile percentage* is the most significant element, in line with the findings in related psychological studies (e.g., Krumhuber et al., 2007). Overall, the results support that team confidence has a significant effect on the amount raised, which is not totally derived from the visual perception of *Suit percentage*, *Smile percentage*, or *Black and white image*.

Insert Table 7 About Here

3.1.2 Causality and endogeneity

The ideal setting for establishing the causality between firm characteristics (e.g., confidence of the management team) and investors' interest (e.g., amount of capital raised as a result of their willingness to invest) would compare an investor's reaction to two identical firms that differ only in the characteristic of interest. Unfortunately, such a setting is not feasible using observational data.

First, we consider possible concerns about reverse causality. The relation we have established so far using our analyses between confidence and the outcome of ICOs may be endogenous since higher quality projects might make proponents look more confident and attract more investors. Management team members might indeed appear more confident when their private information on the project is more positive. While our previous analyses controlled for a number of characteristics of the firms and of their teams, we now focus specifically on the determinants of confidence to identify a potential instrument to implement an instrumental variable regression. We do so by referring first to the large psychology and education literature that documents that early childhood experiences affect the level of confidence of an individual (e.g., Holman and Silver, 1998; Labonté et al., 2012; Nelson, 1993). In particular, a number of studies have documented the long-lasting behavioral effects of relative age differences at the start of formal schooling.[12] Because education systems have a single cut-off date for school eligibility, a continuum of ages exists within each starting class. For example, a one year of age range relative to the age of school entry results in some pupils being 20% older than others when they begin school. This evidence might be linked to observational learning, whereby agents may learn from their peers about what they can achieve (Manski, 2000). Hence, individuals' confidence benefits from a rank effect of being paired with peers slightly weaker than them (Battaglini et al., 2005). There is a robust evidence that this maturity advantage of being older in a cohort is linked to higher levels of confidence (e.g., Fenzel, 1992; Thompson et al., 1999, 2004).

We address endogeneity by employing an instrumental variable approach using a two-stage least squares regression. We use relative age, defined by birthdate in relation to school entry cut-off dates, as an instrument in the first stage. We obtain the year-by-year state school

[12] The relative age effect was first demonstrated in the education system. Early psychology research revealed that young people who demonstrated eminent performance tended to be born early in their year of birth (Huntington, 1938; Kassel, 1929; Pintner and Forlano, 1934). Subsequent studies have revealed that the relative age effect persists into adulthood (Cobley et al., 2009). Relatively young students display greater health problems (Goodman et al., 2003) and are more likely to suffer from psychological disorders (Morrow et al., 2012) and school victimization (Muehlenweg, 2010). They are overrepresented in statistics about psychiatric support (Sharp et al., 2009) and incidences of suicide (Thompson et al., 1999).

cut-off dates from the Eurydice Report[13] and from Bedard and Dhuey (2012). We search white papers and LinkedIn for the birthdate of the CEO of each ICO in our sample. This instrument satisfies the exclusion restriction (Roberts and Whited, 2012) in that relative age is unlikely to affect the outcome variables (capital rises in an ICO), if not through its relation with the endogenous variable (confidence).

Second, we consider that some characteristics of successful ICOs might be "replicated" in subsequent ICOs to increase the probability of success. Observational learning theory predicts that the importance of others' decisions increases when decision-makers have little information (Bikhchandani et al., 1992). Therefore, proponents of late ICOs could "learn" from previous successful cases.[14] Recent methodological studies have "emphasized the importance of identifying multiple—as opposed to single—instruments" (Semadeni et al., 2014, p. 1078). Accordingly, we adopt a second instrument. Since more confident founders may launch ICOs in different periods to less confident ones, we introduce the *Mimicking behavior* variable, which is defined for each ICO as the average level of confidence in ICOs in the same industry over the previous quarter. Mimicking is a common behavior to achieve social legitimacy (Deephouse, 1996, 2000; Deephouse and Carter, 2005), and it is particularly important for capital raising decisions (Bell et al., 2012; Bertoni et al., 2014). Hirshleifer and Teoh (2018)

[13] See https://eacea.ec.europa.eu/national-policies/eurydice/content/key-data-early-childhood-education-and-care-europe-%E2%80%93-2019-edition_en.

[14] As an additional analysis, we test whether the learning effect has an impact throughout the sample period, namely, that the level of perceived confidence grows with the flow of ICOs over time. To do so, we include the trend effect variable in the visual element analyses. As reported in Table 6, the trend effect is not significant. This means that the level of perceived confidence does not increase from the first to the last ICO in our sample. Additionally, Figure 3 presents the distributions of *Confidence* by year. The graphs show that the perceptions of confidence in ventures are similarly distributed in both years. We run the *t*-test of the difference in means between the sample in 2017 and that in 2018. We obtain a *t*-value of 0.1600 and *p*-value of 0.8729, indicating no statistically significant difference between these two years.

refer to this as social transmission bias and argue that the main social activity is the mimicking of managers toward peer groups.[15]

Table 8 reports the other results of our regressions. In Model 1, we report the first-stage regression result of our instruments. We find that the coefficients of both our instruments (*Relative Age* and *Mimicking Behavior*) are positive and significant at the 10% level. Based on the *F*-statistics in our first stage, we can assume that our instruments are not weak, since the *F*-statistics on the joint significance of instruments are higher than Stock et al.'s (2002) recommended value of 11.59 for both instruments. In Model 2, the coefficient of confidence (i.e., the fitted value from Model 1) remains strongly significant, thereby confirming the role of confidence in shaping the outcome of ICOs.[16]

Insert Table 8 About Here

3.1.3 Different estimation techniques and additional control variables

We next run a set of robustness tests using different estimation techniques and additional control variables. First, we assess the residuals obtained from the main model (Model 4 of Table 4) using a QQ plot, finding that the error terms are approximately normally distributed. However, the Shapiro–Wilk test for normality indicates that the residuals deviate from a normal distribution. To deal with this potential issue, we use a generalized linear model (GLM) to estimate Eq (1). A GLM is a generalization of a linear regression that allows for the dependent variables that have a non-normal error distribution, estimated using maximum likelihood

[15] Examples of finance papers referring to mimicking behavior include Bikhchandani et al. (1992) and Scharfstein and Stein (1990). Cronqvist and Pély (2019, p. 23) define it in the context of social corporate finance, referring to how ideas spread to a group "even though they would not be considered as catchy by an individual in a vacuum." In social psychology, this is referred to as the "birds of a feather" hypothesis.

[16] The number of observations in Table 8 reduces to 106 due to the exclusion of the first six months of the sample period to measure *Mimicking behavior* and to missing information about the birthdate of the CEOs of ICOs to measure *Relative Age*.

estimation. Further, we conduct another robust model that removes high leverage outliers[17] to examine whether the results in the presence of larger and smaller residuals are weighted unequally and thus more efficient than least squares estimators are (Fisch, 2019). The results reported in Models 1 and 2 of Table 9 concur with the main results reported in Table 4. Overall, we find significant evidence to confirm the robustness of our main analysis.

In our sample, 196 of 515 ICOs did not raise funds. To capture the size effect from the amount raised and these unsuccessful ICOs, we consider a two-stage model (Stata command: *twopm*) with probit in the first stage and linear regression in the second stage. The two stage-model is used to estimate the models in which the positive outcome is continuous. Models 3 and 4 of Table 9 report our findings on the relation between success/amount raised and confidence. *Amount raised* is coded one if the funds are raised and zero otherwise for the probit regression, whereas we use the natural log formation of the amount raised for the linear regression. We find that the coefficients of *Confidence* are significantly positive at the 10% level in both models. This result is consistent with the proposition that greater team confidence results in a higher probability of fundraising success and in a higher amount of funds raised in ICOs.

Insert Table 9 About Here

Second, we consider a factor that reflects the fundraising period, which may affect the fundraising amount regardless of the content provided on the campaign site. Ventures can determine how long their ICO campaign should last. Longer campaigns have the potential to obtain more funding since they have more time. We calculate the campaign duration in days

[17] A high leverage outlier is defined as an observation with an extreme value for a predictor variable. Based on Stata's *rreg* function, leverage is a measure of how far an independent variable deviates from its mean. High leverage points can affect the estimate of regression coefficients considerably.

(*Campaign duration*) from the ICO start date to the ICO end date. Model 1 of Table 10 reports the result when *Campaign duration* is included. The result shows that campaign duration does not relate to fundraising. The coefficient of *Confidence* remains positive and significant (*t*-value=2.319).

Besides reading information on an ICO project from a listing website, investors may wish to know detailed information on the project. A white paper is an important avenue to present further plans about the product or service provided by an ICO project (Fisch, 2019). We assign a dummy variable (*White paper*) coded one if an ICO project provides a valid link to the white paper on their Icobench webpage and zero otherwise. This variable measures whether it is convenient for investors to locate the white paper quickly compared with conducting additional research (e.g., checking external websites). We obtain these data from Icobench and then cross-check ICO ventures' websites to clarify the validity of the link for accessing the white paper. With the inclusion of *White paper* (Model 2 of Table 10), the coefficient of *Confidence* is still significant and positively associated with the amount raised. In Model 3, we include both additional variables, *Campaign duration* and *White paper*. The results show that *Confidence* is statistically significant and also has an economically significant effect on the fundraising amount.

Third, ICO fundraising may be more volatile because of the uncertainty of the Bitcoin price (Fisch, 2019). Although there is no significant evidence showing such an effect, we cannot rule out that the ICO market is likely to be affected by speculation and a high Bitcoin price. Thus, we obtain the daily closing Bitcoin price from Coinmarketcap and prepare the variable *Bitcoin* (in 1,000 USD) for an additional robustness test. We re-run our baseline model (Model 4 of Table 4) and report the result in Model 4 of Table 10. In line with Fisch (2019), the coefficient of *Bitcoin* is statistically insignificant. Our main finding is thus qualitatively unchanged: the coefficient of *Confidence* remains positive and significant when including the

Bitcoin price, and the adjusted R-squared value shows no significant change compared with the other specifications.

Fourth, previously in our main analysis we address the location effect by considering a *Location* dummy equal to one if an ICO takes place in the top five countries sorted by the total fundraising amount in our sample. To better account for the disproportionate distribution of investment across countries, we re-define *Location* as the percentage of ICOs by country and re-run our baseline model (Model 4 of Table 4). The regression result is reported in Model 5 of Table 10. In addition, we further re-define *Location* as the percentage of ICOs by country but count only ICOs taking place before the focal ICO in order to exclude ex-post information not available at the moment of the ICO and re-run our baseline model with this re-defined *Location* variable, see the result in Model 6 of Table 10. In both cases, the effect of *Location* remains insignificant. Our main variable of interest *Confidence* remains statistically significant.

Insert Table 10 About Here

Fifth, we collect data on Twitter activity from Icobench, which monitors the Twitter account of each ICO and evaluates its activity levels using an algorithm. To investigate the Twitter activity effect in a more transparent way, in line with Fisch (2019), we collect 267,101 tweets from each sample venture's official Twitter account (from their first tweet to the latest tweet). In addition to a general measure capturing the number of tweets sent from a venture's Twitter profile (Fisch, 2019), we select tweets for each ICO during their offering period.[18] We then conduct text mining and compute the following three measurements:

- *Tweets.* Average number of tweets (per day) over the campaign period. This enables us to measure the overall activity level of the ICO's Twitter content.

[18] We also select tweets for each ICO before their offering campaigns. The results are qualitatively similar to the analyses reported in Table 11.

- *Re-tweets.* Average number of re-tweets (per day) over the campaign period. This enables us to measure the interaction level with other users' Twitter content.
- *Mention others.* Average number of tweets (per day) that mention other Twitter users. This enables us to measure the communication level with other users.

Table 11 replicates our baseline model (Model 4 of Table 4) by replacing the variable *Twitter* with each of the three alternative Twitter activity variables above. The bottom of Table 11 also reports the correlation matrix between these variables. Since *Tweets* is highly correlated with *Mention others*, we do not include all three variables in one regression. Instead, we test a model including *Tweets* and *Re-tweets* (Model 4) and another including *Re-tweets* and *Mention others* (Model 5). The estimates for these tests are consistent with the findings reported in Table 4.

Insert Table 11 About Here
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4. Conclusions

This study investigates the relation between team members' confidence and the amount of capital raised through ICOs. The environment of capital raising for blockchain-based ventures contains a high level of asymmetric information toward prospective investors. As a result, a certain form of information may significantly affect financing outcomes. We document new evidence that confidence matters to fundraising, indicating that visual information is also crucial when ventures introduce themselves to the public on online platforms.

Specifically, we conduct an experiment asking participants to judge the confidence of team members based on their photographs and test whether a significant relationship between perceived confidence and the fundraising amount exists. We find that a higher level of confidence of team members is associated with a higher fundraising amount. The results support the view that photographs can show more than expected. This result is robust to other visual traits, suggesting that confidence has distinct effects from attractiveness and intelligence.

Overall, this study contributes to the literature on the link between managerial traits and finance by showing a positive association between management teams' confidence and capital raising. By identifying visual elements, picture cues serve as alternative information channels to help investors make investment decisions in a financial market with high information asymmetries and barriers. This study thus opens potential avenues of exploration for behavioral economics and ecological rationality in economics inspired by pioneers such as Gigerenzer (2008), Kahneman (2003), Simon (1979), Smith (2003), and Tversky and Kahneman (1981).

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Figure 1

Examples of the pictures of the six teams used in the experiment.

For an ICO team, the team picture is generated by concatenating the individual member profile pictures, which can be publicly downloaded from Icobench. For members with no face pictures available, a default gray profile picture provided by Icobench is used (as shown in Figure 1c). Face information in pictures is mosaicked here for illustration purposes because of privacy concerns, but clear pictures are used in the experiment.

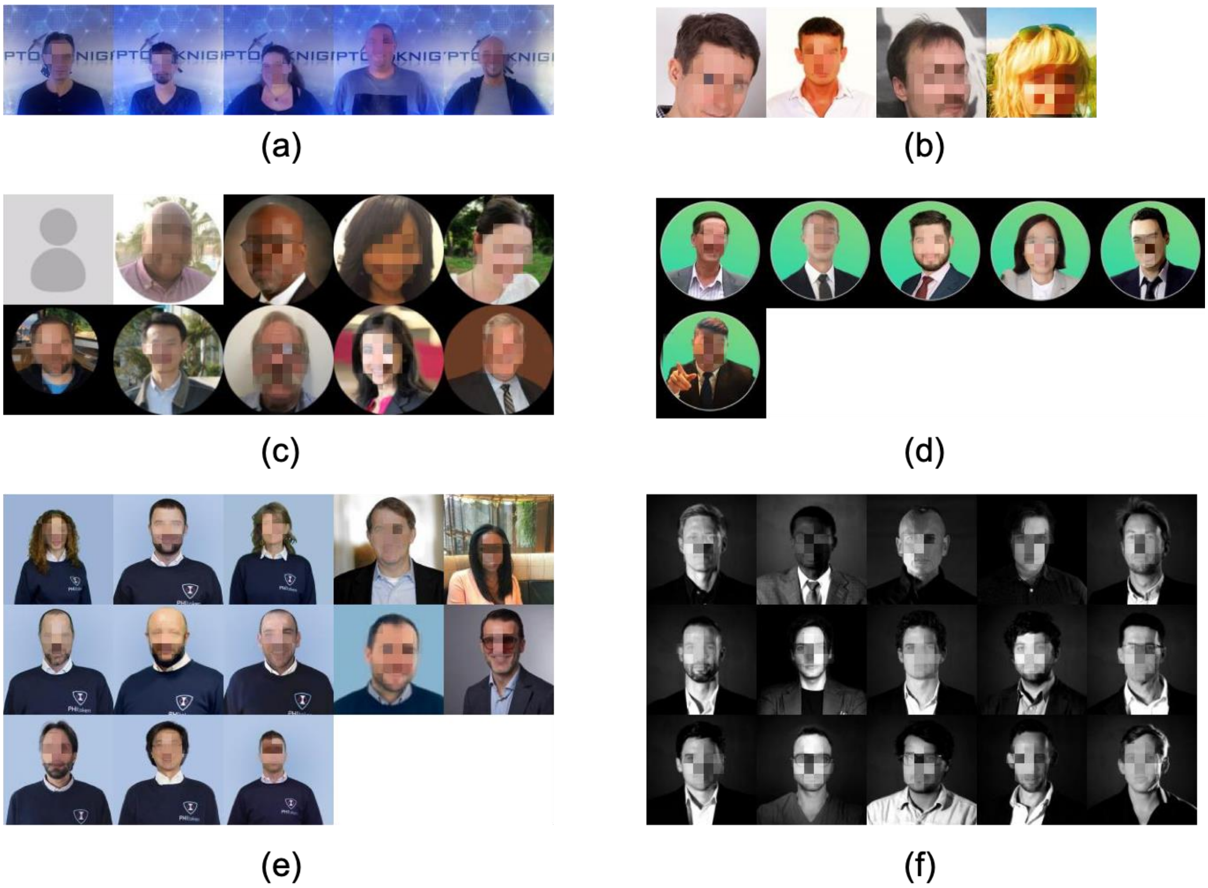
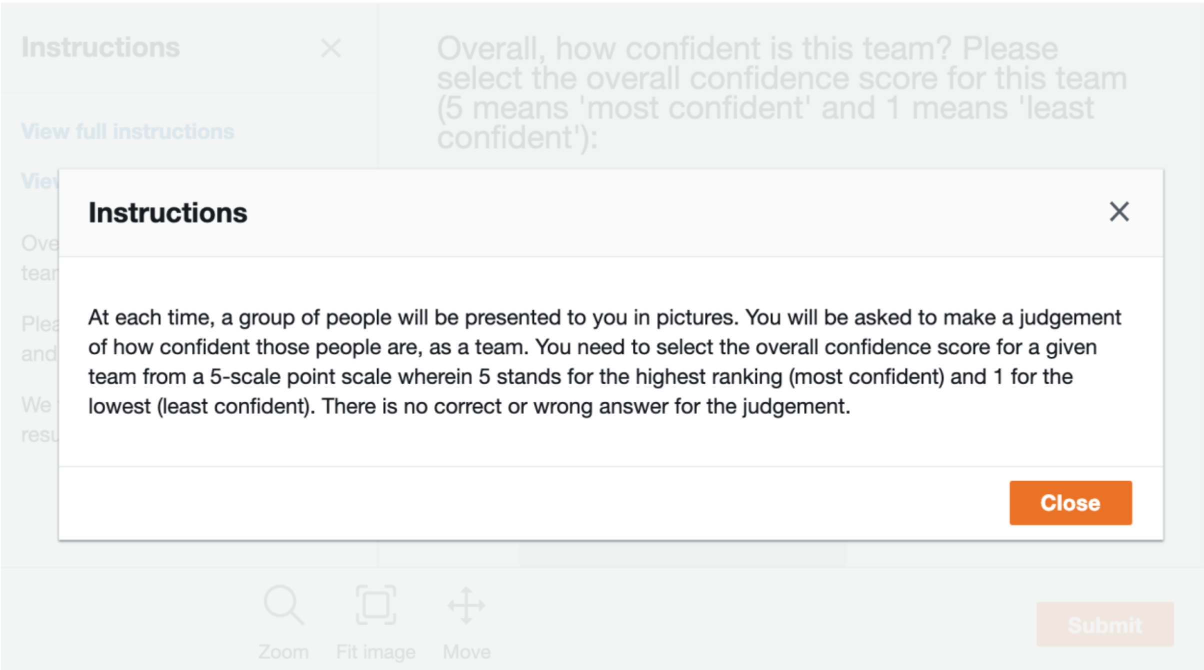


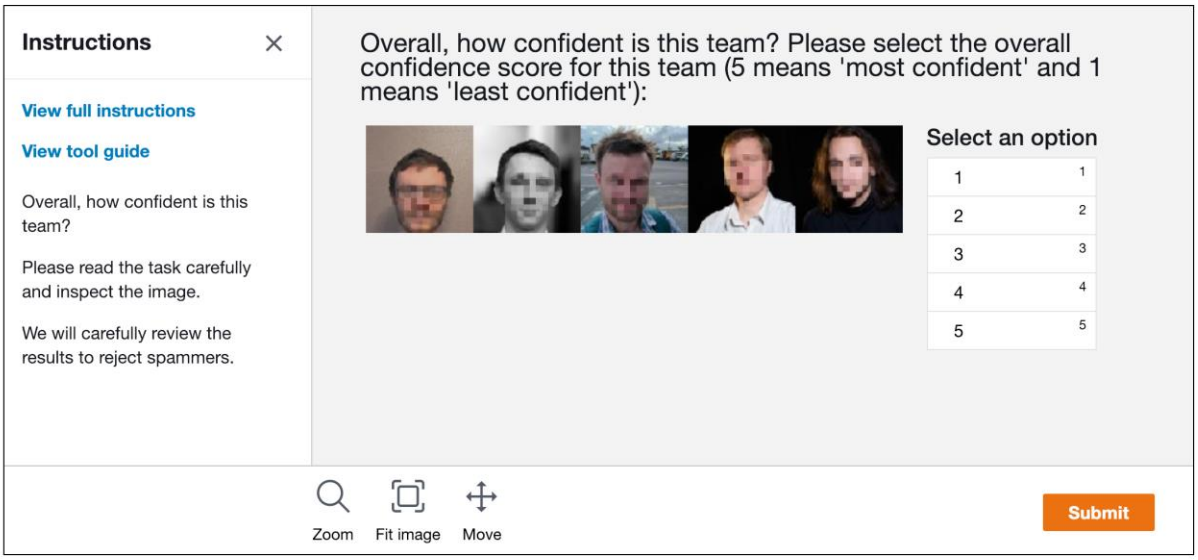
Figure 2

Illustration of the experimental design.

This figure shows the interface participants used to evaluate the team pictures on mTurk. Figure 2a presents the instructions shown to participants before conducting the picture evaluation work. A participant is shown a team picture and asked to select the overall confidence score on a five-point scale for this team based on the picture (see Figure 2b). Participants can view the instructions at any time during the experiment by clicking the "view full instructions" link. The "view tool guide" link provides instructions on how to use the image tools (i.e., zoom, fit image, and move) at the bottom of the interface, allowing participants to check the picture details. Participants are asked "how confident is this team" or "make a judgment of how confident are those people as a team" rather than "how confident do you feel this team is."



(a)



(b)

Figure 3
Team confidence distribution by year.
The variable *Confidence* is based on the average value of the ratings from mTurk participants who evaluate the overall confidence of the team based purely on the team picture. The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias. There are 113 and 402 ventures in 2017 and 2018, respectively. The mean difference *t*-value is 0.1600 with a *p*-value of 0.8729, showing no statistically significant difference between samples' confidence in these two periods.

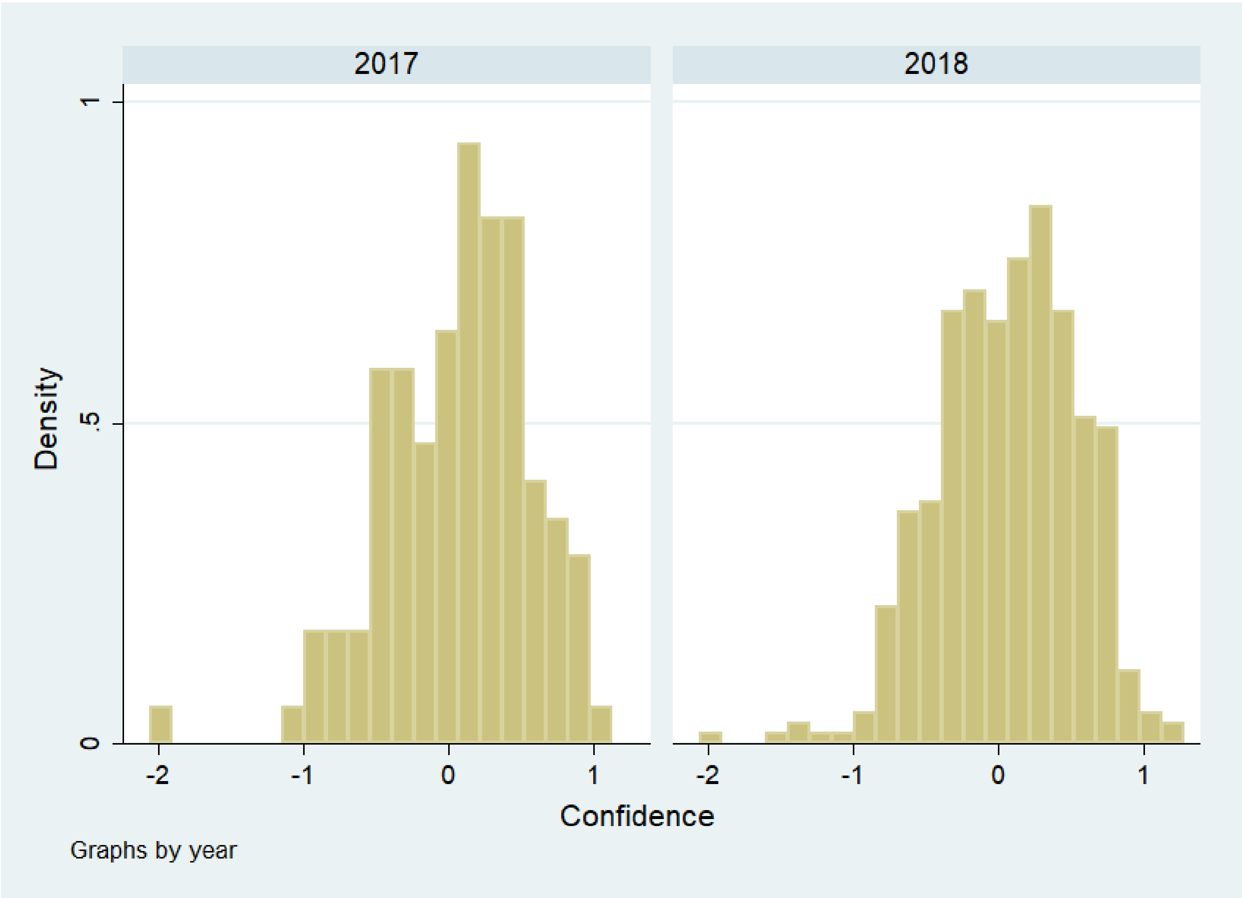


Table 1

Experimental design details and visual score correlations.

This table reports the experimental design details (Panel A) and correlation matrix of the visual scores calculated from the responses of mTurk participants. HIT stands for "Human Intelligence Task," which is defined by the mTurk platform to refer to a task on which a participant can work and submit a response. The HIT approval rate is the rate that requesters (i.e., the people who set the experiment) have approved the HITs that participants complete. A requester can reject a HIT if the quality of the participant response (i.e., data) is low. Our experiment requests participants to have experience of more than 1,000 HITs and an approval rate greater than 95% to guarantee the quality of the response data. Participants are restricted to being from ICO-active countries in which at least five ICOs (66% in our sample) are completed during our sample period (from January 2017 to June 2018). Each trait is assessed by a large number of mTurk participants to reduce bias. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Experiment setting	
Reward per evaluation (picture)	$0.05
Qualification of participants	HIT Approval Rate (%) for all Requesters' HITs greater than 95
Experience of participants	Finished number of HITs approved greater than 1000
Location of participants	US, UK, Singapore, Russia, Switzerland, Estonia, HK, Australia, Canada, Germany, Slovenia, Netherlands, UAE, Latvia, Malta, Japan, Ukraine, Belize, France, South Africa
Number of participants	357

Panel B: Correlations and mean VIFs					
	a	b	c	mean VIF	VIF is estimated from
a Confidence	1	-	-	2.10	Model 4 of Table 4
b Attractiveness	0.24***	1	-	2.06	Model 1 of Table 5
c Intelligence	0.43***	0.26***	1	2.11	Model 2 of Table 5

Table 2

Descriptive statistics

This table shows the summary statistics of the variables used in our regression analyses. Variable definitions are summarized in Appendix A. Our sample contains 515 ICO campaigns from Icobench from January 2017 to June 2018.

	Mean	Min	Median	Max	S.D.	N
Amount raised (in mil USD)	8.04	0.00	1.93	157.89	13.61	515
Amount raised (in ln)	9.63	0.00	14.48	18.88	7.67	515
Main independent variable:						
Confidence	0.07	-2.05	0.11	1.28	0.49	515
Control variables:						
Team size	14.21	1.00	13.00	67.00	8.38	515
Team size squared	271.95	1.00	169.00	4489	386.31	515
Member names	1.00	0.56	1.00	1.00	0.02	515
Pre-sale	0.58	0.00	1.00	1.00	0.49	515
Hardcap_ln	16.70	10.61	16.81	23.33	1.27	515
Offered ownership	0.58	0.01	0.60	1.00	0.21	515
Offered tokens	16.02	0.00	18.27	27.85	6.65	515
Ethereum	0.88	0.00	1.00	1.00	0.32	515
Twitter	0.74	0.00	0.00	3.00	1.20	515
Female percentage	0.13	0.00	0.12	0.67	0.11	515
Location	0.46	0.00	0.00	1.00	0.50	515
Trend effect	258.00	1.00	261.00	515.00	148.80	515
Other team visual characteristics:						
Attractiveness	0.07	-1.50	0.13	2.03	0.48	515
Intelligence	0.07	-1.78	0.12	1.23	0.46	515
Additional controls for robustness:						
Campaign duration	40.88	1.00	31.00	222.00	30.15	515
White paper	0.56	0.00	1.00	1.00	0.50	515
Visual elements variables:						
Glasses percentage	2.47	0.00	2.00	17.00	2.28	515
Suit percentage	4.89	0.00	4.00	22.00	4.14	515
Smile percentage	4.12	0.00	3.00	32.00	3.44	515
Crossed arms	0.47	0.00	0.00	18.00	1.35	515
Face proportion	0.16	0.04	0.15	0.48	0.06	515
Same place	0.17	0.00	0.00	1.00	0.38	515
Same clothes	0.03	0.00	0.00	1.00	0.18	515
Uniform background	0.19	0.00	0.00	1.00	0.39	515
Black and white image	0.27	0.00	0.00	1.00	0.44	515

Table 3

Correlation matrix.

This table reports the correlation matrix between the main variables used in the regression analysis. The estimated VIFs are based on Model 4 of Table 4. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Amount raised (in ln)	1												
2	Confidence	0.21***	1											
3	Team size	0.32***	0.22***	1										
4	Team size squared	0.25***	0.12**	0.92***	1									
5	Member names	-0.02	0.01	0.04	0.03	1								
6	Pre-sale	0.03	0	0.11*	0.05	-0.05	1							
7	Hardcap_ln	0.09*	0.12**	0.19***	0.15***	0.02	-0.02	1						
8	Offered ownership	-0.13**	-0.10*	-0.14**	-0.14**	0.08	-0.02	-0.02	1					
9	Offered tokens	0.16***	0.12**	0.12**	0.09*	-0.01	0.08	0.05	-0.18***	1				
10	Ethereum	0.02	-0.01	-0.01	-0.01	-0.02	0.06	0.02	0.02	-0.07	1			
11	Twitter	0.35***	0.10*	0.24***	0.17***	0.01	0.01	0.06	-0.17***	0.08	0.06	1		
12	Female percentage	-0.08	0	0.14**	0.11*	0.04	0.04	-0.02	0.09*	0	-0.03	-0.02	1	
13	Location	0.03	0.03	-0.02	-0.04	-0.06	-0.08	-0.02	-0.04	0	0.03	0	0.02	1
14	Trend effect	-0.12**	-0.02	0.09	0.05	0.01	0.24***	-0.01	-0.06	0.02	0.04	-0.04	0.07	-0.15***
15	Attractiveness	0.17***	0.24***	0.22***	0.15***	0.10*	0.03	-0.01	0.04	0.06	0.08	0.12**	0.22***	-0.02
16	Intelligence	0.19***	0.43***	0.35***	0.25***	-0.03	0.04	0.13**	-0.10*	0.19***	0.06	0.16***	0.08	-0.02
17	Campaign duration	-0.13**	-0.13**	-0.10*	-0.09*	0.02	-0.07	0.02	0.05	-0.11*	-0.04	-0.14**	0.08	0.05
18	White paper	0.15***	-0.03	0.01	-0.03	0.01	0.05	0.02	-0.06	-0.08	0.11*	0.13**	-0.09*	-0.01
19	Glasses percentage	0.20***	0.21***	0.57***	0.48***	0.03	0.06	0.10*	-0.19***	0.17***	-0.07	0.18***	0.01	-0.02
20	Suit percentage	0.23***	0.26***	0.67***	0.59***	0.02	0.07	0.21***	-0.07	0.14***	0	0.14***	0.02	0.01
21	Smile percentage	0.29***	0.37***	0.66***	0.61***	0.04	0.08	0.15***	-0.17***	0.17***	-0.02	0.21***	0.16***	0
22	Crossed arms	0.05	0.10*	0.26***	0.25***	0.04	0.04	0.03	-0.08	0.02	0.03	0.07	0.05	-0.01
23	Face proportion	-0.06	-0.09*	-0.01	0	-0.07	0.11*	0.09*	-0.08	0.04	0.07	0.01	-0.06	-0.01
24	Same place	0.12**	0.08	0.17***	0.18***	0.03	0	0.05	-0.05	0.02	-0.01	0.08	0.04	-0.03

25	Same clothes	0.01	0.05	0.16***	0.18***	0.02	-0.02	0.05	0	-0.05	0.03	0.03	0.07	0.02
26	Uniform background	0.03	0.06	0.01	0.05	0.03	-0.08	0.06	0.09*	0	-0.06	-0.02	-0.04	-0.04
27	Black and white image	0	0.11*	0.03	0	-0.05	0.04	0.05	0.01	0.03	0.03	0.05	0	-0.04
		14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
15	Attractiveness	0.06	1											
16	Intelligence	0.11*	0.26***	1										
17	Campaign duration	-0.09*	-0.09*	-0.09*	1									
18	White paper	-0.09	0.03	0.01	-0.03	1								
19	Glasses percentage	0.10*	0.03	0.35***	-0.15***	0.02	1							
20	Suit percentage	0.06	0.12**	0.43***	0	0.06	0.48***	1						
21	Smile percentage	0.07	0.17***	0.30***	-0.14**	0.04	0.43***	0.43***	1					
22	Crossed arms	0.13**	0.15***	0.17***	-0.05	0.03	0.18***	0.19***	0.21***	1				
23	Face proportion	-0.01	-0.14**	-0.10*	0.03	0.05	0	-0.05	-0.02	-0.26***	1			
24	Same place	0.01	0.15***	0.13**	-0.06	0.05	0.09*	-0.05	0.18***	0.24***	-0.28***	1		
25	Same clothes	0.14**	0.10*	0.03	-0.01	-0.08	0.04	0.02	0.20***	0.26***	-0.19***	0.35***	1	
26	Uniform background	0.01	-0.02	0.12**	-0.01	0.05	0.04	0.01	0.04	0.04	-0.15***	0.24***	0.13**	1
27	Black and white image	0.05	0.09*	0.11*	-0.02	0.04	0.05	0.06	0.06	-0.05	0.14**	-0.09*	-0.11*	0.07

Table 4

Team confidence and ICO fundraising.

This table reports the results of the OLS regressions with the four specifications in Models 1 to 4 (i.e., no time effect, year fixed effect, quarter fixed effect, and inclusion of the trend variable *Trend effect*). The dependent variable is the ICO fundraising amount (natural logarithm). The main independent variable of interest is *Confidence,* which is based on the average value of the ratings from mTurk participants who evaluate the overall confidence of the team based purely on the team picture. The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
Confidence	1.642**	1.632**	1.424**	1.546**
	(2.573)	(2.564)	(2.266)	(2.492)
Team size	0.394***	0.400***	0.457***	0.429***
	(4.219)	(4.244)	(4.950)	(4.711)
Team size squared	-0.004**	-0.004**	-0.005***	-0.005***
	(-2.377)	(-2.393)	(-3.101)	(-2.803)
Member names	-8.300	-8.530	-5.775	-7.553
	(-0.750)	(-0.771)	(-0.607)	(-0.758)
Pre-sale	-0.159	-0.047	0.495	0.294
	(-0.255)	(-0.073)	(0.763)	(0.456)
Hardcap_ln	0.053	0.049	0.064	0.037
	(0.211)	(0.195)	(0.265)	(0.155)
Offered ownership	-0.506	-0.662	-0.103	-0.907
	(-0.330)	(-0.424)	(-0.066)	(-0.585)
Offered tokens	0.105**	0.104**	0.110**	0.104**
	(2.119)	(2.105)	(2.310)	(2.155)
Ethereum	0.262	0.308	0.330	0.379
	(0.266)	(0.312)	(0.353)	(0.400)
Twitter	1.655***	1.635***	1.471***	1.582***
	(6.902)	(6.793)	(6.153)	(6.578)
Female percentage	-7.872***	-7.654***	-7.576***	-7.314***
	(-2.952)	(-2.835)	(-2.850)	(-2.738)
Location	0.367	0.294	0.123	0.064
	(0.602)	(0.480)	(0.202)	(0.106)
Trend effect	-	-	-	-0.007***
	-	-	-	(-3.234)
Constant	10.497	10.718	6.732	11.532
	(0.895)	(0.900)	(0.654)	(1.080)
Time effect	No	Years	Quarters	Trend
Observations	515	515	515	515
Adjusted R-squared	0.209	0.208	0.245	0.225

Table 5

Analyses including attractiveness and intelligence.

This table reports the results of the OLS regression of team members' confidence variable and the ICO fundraising amount with additional personal traits (attractiveness and intelligence). Similar to *Confidence*, *Attractiveness* (*Intelligence*) is based on the average value of the ratings from mTurk participants who evaluate the overall attractiveness (intelligence) of the team based purely on the team picture. The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses.

	(1)	(2)	(3)
Confidence	1.270**	1.527**	1.307*
	(1.964)	(2.277)	(1.905)
Attractiveness	1.432**	-	1.444**
	(2.106)	-	(2.110)
Intelligence	-	0.061	-0.126
	-	(0.082)	(-0.168)
Team size	0.401***	0.427***	0.405***
	(4.433)	(4.542)	(4.338)
Team size squared	-0.004***	-0.005***	-0.004***
	(-2.716)	(-2.750)	(-2.701)
Member names	-9.966	-7.492	-10.112
	(-1.054)	(-0.750)	(-1.054)
Pre-sale	0.321	0.296	0.316
	(0.501)	(0.458)	(0.491)
Hardcap_ln	0.074	0.037	0.075
	(0.313)	(0.153)	(0.319)
Offered ownership	-1.134	-0.906	-1.139
	(-0.746)	(-0.584)	(-0.747)
Offered tokens	0.101**	0.104**	0.102**
	(2.096)	(2.135)	(2.106)
Ethereum	0.198	0.372	0.209
	(0.208)	(0.389)	(0.219)
Twitter	1.545***	1.581***	1.547***
	(6.428)	(6.567)	(6.433)
Female percentage	-8.466***	-7.325***	-8.453***
	(-3.182)	(-2.736)	(-3.172)
Location	0.091	0.066	0.089
	(0.151)	(0.108)	(0.146)
Trend effect	-0.007***	-0.007***	-0.007***
	(-3.331)	(-3.234)	(-3.308)
Constant	14.062	11.513	14.123
	(1.380)	(1.078)	(1.373)
Observations	515	515	515
Adjusted R-squared	0.231	0.224	0.229

Table 6
Visual elements analyses.
This table reports the multiple linear regression results of the relation between the visual elements and *Confidence*. For a better comparison, the results of the relations between the visual elements and *Attractiveness* and *Intelligence* are also reported. *Confidence* is based on the average value of the ratings from mTurk participants who evaluate the overall confidence of the team based purely on the team picture. The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias. Similarly, *Attractiveness* (*Intelligence*) is based on participants' judgment of attractiveness (intelligence) on a team purely from a team picture. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses.

	(1) Confidence	(2) Attractiveness	(3) Intelligence
Glasses percentage	0.007	-0.034***	0.026***
	(0.579)	(-3.551)	(3.246)
Suit percentage	0.020***	-0.001	0.036***
	(3.010)	(-0.216)	(6.075)
Smile percentage	0.056***	0.003	0.011
	(7.939)	(0.446)	(1.637)
Crossed arms	0.006	0.022**	0.016
	(0.604)	(2.281)	(1.226)
Face proportion	-0.593	-0.903**	-0.281
	(-1.540)	(-2.304)	(-0.759)
Same place	0.044	0.115**	0.140***
	(0.755)	(2.049)	(2.618)
Same clothes	0.013	0.043	-0.141
	(0.115)	(0.377)	(-1.424)
Uniform background	0.042	-0.057	0.114**
	(0.723)	(-1.044)	(2.258)
Black and white image	0.095**	0.123***	0.074*
	(2.257)	(2.866)	(1.747)
Team size	0.017**	0.034***	0.020***
	(2.359)	(3.543)	(2.885)
Team size squared	-0.001***	-0.000**	-0.001***
	(-4.605)	(-2.395)	(-4.113)
Female percentage	-0.244	0.687***	0.217
	(-1.200)	(3.496)	(1.321)
Trend effect	-0.000	0.000	0.000
	(-1.538)	(0.365)	(1.275)
Constant	-0.209**	-0.211*	-0.461***
	(-2.189)	(-1.831)	(-4.849)
Observations	515	515	515
Adjusted R-squared	0.203	0.136	0.269

Table 7

Auxiliary regressions for visual elements analyses.

This table reports the results of the OLS regressions. Model 1 estimates the relation of the ICO amount raised with *Visual elements residuals*, as measured in Model 1 of Table 6. Model 2 regresses the ICO amount raised on *Confidence* including the three significant visual elements, namely, *Suit percentage*, *Smile percentage*, and *Black and white image*, estimated in Model 1 of Table 6, and the control variables. Models 3 to 5 re-run the baseline model (Model 4 of Table 4) by replacing *Confidence* with one of those three significant visual elements. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Visual elements res.	1.162*	-	-	-	-
	(1.766)	-	-	-	-
Confidence	-	1.296**	-	-	-
	-	(2.014)	-	-	-
Suit percentage	-	-0.039	-0.025	-	-
	-	(-0.442)	(-0.285)	-	-
Smile percentage	-	0.200*	-	0.268***	-
	-	(1.889)	-	(2.628)	-
Black and white image	-	-0.657	-	-	-0.470
	-	(-0.957)	-	-	(-0.687)
Team size	0.493***	0.413***	0.504***	0.430***	0.495***
	(5.632)	(4.131)	(5.211)	(4.585)	(5.527)
Team size squared	-0.006***	-0.005***	-0.006***	-0.006***	-0.006***
	(-3.486)	(-2.981)	(-3.366)	(-3.421)	(-3.397)
Member names	-7.345	-8.870	-7.561	-8.341	-7.960
	(-0.729)	(-0.866)	(-0.759)	(-0.847)	(-0.774)
Pre-sale	0.262	0.284	0.227	0.230	0.237
	(0.406)	(0.442)	(0.353)	(0.359)	(0.368)
Hardcap_ln	0.057	0.047	0.083	0.055	0.085
	(0.241)	(0.196)	(0.355)	(0.234)	(0.361)
Offered ownership	-0.998	-0.652	-1.106	-0.832	-1.099
	(-0.640)	(-0.417)	(-0.706)	(-0.533)	(-0.701)
Offered tokens	0.110**	0.100**	0.113**	0.102**	0.113**
	(2.282)	(2.069)	(2.354)	(2.120)	(2.365)
Ethereum	0.359	0.434	0.380	0.423	0.395
	(0.377)	(0.457)	(0.396)	(0.442)	(0.410)
Twitter	1.593***	1.558***	1.580***	1.542***	1.591***
	(6.584)	(6.490)	(6.489)	(6.406)	(6.549)
Female percentage	-7.565***	-7.977***	-7.605***	-8.183***	-7.541***
	(-2.836)	(-2.941)	(-2.805)	(-3.046)	(-2.813)
Location	0.071	0.040	0.082	0.060	0.064
	(0.116)	(0.065)	(0.134)	(0.098)	(0.105)
Trend effect	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(-3.329)	(-3.214)	(-3.322)	(-3.360)	(-3.281)

Constant	10.550	12.560	10.335	11.528	10.788
	(0.979)	(1.151)	(0.970)	(1.092)	(0.985)
Observations	515	515	515	515	515
Adjusted R-squared	0.221	0.226	0.217	0.225	0.217

Table 8

Instrumental variable model.

This table reports the results of the instrumental variable model. We use a two-stage least squares regression in which the endogenous variable is confidence and the instruments are *Relative age* and *Mimicking behavior*. *Relative age* is defined as the difference in the birthdate of CEOs relative to school entry cut-off dates. *Mimicking behavior* is defined for each ICO as the average level of confidence in ICOs in the same industry over the previous quarter. Model 1 shows the first-stage model with two instruments. Model 2 reports the second-stage result with the fitted value of *Confidence* from Model 1. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses.

	(1)	(2)
	Confidence	Amount raised
Confidence	-	14.901***
	-	(2.84)
Relative age	0.185*	-
	(1.65)	-
Mimicking behavior	0.511*	-
	(1.92)	-
Team size	0.054**	-0.184
	(2.35)	(-0.42)
Team size squared	-0.001*	0.007
	(-1.89)	(0.71)
Pre-sale	0.085	0.315
	(0.67)	(0.18)
Hardcap_ln	0.051	-0.602
	(0.93)	(-0.72)
Offered ownership	0.079	-1.673
	(0.27)	(-0.39)
Offered tokens	0.010	-0.094
	(1.19)	(-0.75)
Ethereum	-0.266	8.566***
	(-1.39)	(2.82)
Twitter	0.042	1.082*
	(0.99)	(1.69)
Female percentage	0.166	-16.996**
	(0.32)	(-2.22)
Trend effect	-0.001**	-0.007
	(-2.14)	(-0.90)
Constant	-1.518	11.904
	(-1.45)	(0.75)
Observations	106	106
Adjusted R-squared	0.039	0.296
Tests for weak instruments, over-identification, and under-identification:		
Over Id. test (p-value)	0.000 (0.9909) (H_0: instruments are valid)	

First stage F-stat (p-value)	4.54 (0.0132)
Under Id. test (p-value)	9.624 (0.0081) (H_0: the model is not identified)
Test of exog. (p-value)	0.000 (0.9909) (H_0: instruments are valid)

Table 9
Robustness tests with different estimation techniques.
This table reports the results of the regressions with the ICO fundraising amount (natural logarithm) as the dependent variable. Model 1 applies a GLM as an alternative estimation technique. Model 2 applies a robust regression estimation to remove high leverage outliers. Models 3 and 4 are the results of a two-stage model with probit in the first stage and OLS in the second stage. The two-stage model is used to estimate the models in which the positive outcome is continuous. In the first stage, the dummy variable as the dependent variable (*Amount raised*) is coded one if the funds are raised and zero otherwise. In the second stage, the dependent variable is the natural log of the amount raised. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses for Models 1 and 2, while robust standard errors are reported in parentheses for Models 3 and 4.

	GLM	Robust	1st stage (Probit)	2nd stage (OLS)
	(1) Amount raised	(2) Amount raised	(3) Amount raised dummy	(4) Amount raised
Confidence	1.546**	1.709**	0.264*	0.340*
	(2.524)	(2.425)	(0.135)	(0.190)
Team size	0.429***	0.492***	0.0709***	0.106***
	(4.772)	(4.496)	(0.019)	(0.030)
Team size squared	-0.005***	-0.006**	-0.001*	-0.002***
	(-2.840)	(-2.521)	(0.000)	(0.001)
Member names	-7.553	-7.034	-1.745	0.160
	(-0.768)	(-0.503)	(1.964)	(2.627)
Pre-sale	0.294	0.335	0.0507	-0.0129
	(0.462)	(0.488)	(0.130)	(0.180)
Hardcap_ln	0.037	0.014	-0.0428	0.408***
	(0.156)	(0.055)	(0.0486)	(0.0819)
Offered ownership	-0.907	-1.379	0.0507	-1.632***
	(-0.592)	(-0.849)	(0.306)	(0.396)
Offered tokens	0.104**	0.113**	0.0179*	0.0128
	(2.183)	(2.254)	(0.00932)	(0.0148)
Ethereum	0.379	0.324	0.120	0.00319
	(0.405)	(0.319)	(0.186)	(0.235)
Twitter	1.582***	1.658***	0.324***	0.156***
	(6.662)	(5.816)	(0.061)	(0.058)
Female percentage	-7.314***	-7.798***	-1.557***	0.263
	(-2.774)	(-2.617)	(0.553)	(0.996)
Location	0.064	0.175	-0.0138	0.0505
	(0.107)	(0.265)	(0.125)	(0.166)
Trend effect	-0.007***	-0.008***	-0.001***	-0.002***
	(-3.275)	(-3.411)	(0.000)	(0.001)
Constant	11.532	11.237	1.823	8.226***
	(1.094)	(0.771)	(2.111)	(2.880)

Observations	515	515	515	319
Chi^2	238.7			
Adjusted/Pseudo R^2		0.226	0.172	0.292

Table 10

Robustness tests with additional or different control variables.

This table reports the results of the regressions with the ICO fundraising amount in natural logarithm as the dependent variable. For Models 1-4, we re-run the baseline model (Model 4 of Table 4) by including additional variables: Model 1 includes an additional control variable, *Campaign duration*, defined as the campaign period in days from the ICO start date to the ICO end date; Model 2 includes an additional control variable, *White paper*, defined as a dummy variable coded one if the ICO project provides a valid link to the white paper on the Icobench webpage and zero otherwise; Model 3 is the regression including both the above-mentioned additional variables; Model 4 is the regression including the Bitcoin price (*Bitcoin*) in 1,000 USD. For Models 5-6, we re-run the baseline model (Model 4 of Table 4) by redefining *Location* with alternative definitions: In Model 5, we measure *Location* as the percentage of ICOs by country; in Model 6, we measure *Location* as the percentage of ICOs by country but count only ICOs taking place before the focal ICO. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Confidence	1.450**	1.646***	1.553**	1.577**	1.532**	1.560**
	(2.319)	(2.682)	(2.515)	(2.514)	(2.477)	(2.509)
Campaign duration	-0.014	-	-0.013	-	-	-
	(-1.359)	-	(-1.299)	-	-	-
White paper	-	1.575**	1.553**	-	-	-
	-	(2.526)	(2.489)	-	-	-
Bitcoin	-	-	-	-0.058	-	-
	-	-	-	(-0.553)	-	-
Team size	0.432***	0.404***	0.407***	0.430***	0.431***	0.429***
	(4.738)	(4.388)	(4.416)	(4.708)	(4.734)	(4.705)
Team size squared	-0.005***	-0.004**	-0.004**	-0.005***	-0.005***	-0.005***
	(-2.888)	(-2.435)	(-2.517)	(-2.772)	(-2.846)	(-2.814)
Member names	-7.273	-8.361	-8.084	-7.645	-7.142	-7.683
	(-0.741)	(-0.758)	(-0.743)	(-0.775)	(-0.719)	(-0.775)
Pre-sale	0.265	0.194	0.168	0.319	0.301	0.288
	(0.411)	(0.303)	(0.263)	(0.492)	(0.469)	(0.448)
Hardcap_ln	0.055	0.031	0.048	0.042	0.031	0.038
	(0.230)	(0.131)	(0.203)	(0.176)	(0.132)	(0.159)

Offered ownership	-0.954	-0.644	-0.692	-0.910	-0.805	-0.949
	(-0.619)	(-0.417)	(-0.452)	(-0.585)	(-0.522)	(-0.618)
Offered tokens	0.099**	0.115**	0.110**	0.105**	0.102**	0.104**
	(2.052)	(2.454)	(2.352)	(2.173)	(2.118)	(2.154)
Ethereum	0.335	0.153	0.114	0.393	0.337	0.400
	(0.352)	(0.162)	(0.121)	(0.414)	(0.354)	(0.423)
Twitter	1.538***	1.517***	1.477***	1.575***	1.573***	1.582***
	(6.346)	(6.339)	(6.124)	(6.563)	(6.549)	(6.622)
Female percentage	-6.992***	-6.739**	-6.442**	-7.311***	-7.301***	-7.343***
	(-2.620)	(-2.528)	(-2.415)	(-2.731)	(-2.741)	(-2.740)
Location	0.093	0.106	0.132	0.066	3.809	-1.270
	(0.152)	(0.174)	(0.218)	(0.108)	(0.756)	(-0.329)
Trend effect	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(-3.335)	(-2.964)	(-3.065)	(-3.281)	(-3.195)	(-3.299)
Constant	11.728	11.482	11.668	12.097	10.936	11.823
	(1.114)	(0.986)	(1.015)	(1.134)	(1.032)	(1.117)
Observations	515	515	515	515	515	515
Adjusted R-squared	0.227	0.234	0.235	0.224	0.226	0.225

Table 11

Robustness tests with alternative variables for Twitter activity.

This table reports the results of the OLS regressions when replacing the variable *Twitter* used in Table 4 with three alternative variables to capture Twitter activity: (1) *Tweets.* Average number of tweets (per day) over the campaign period to measure the overall activity level of the ICO's Twitter content; (2) *Re-tweets.* Average number of re-tweets (per day) over the campaign period to measure the interaction level with other users' Twitter content; and (3) *Mention others.* Average number of tweets (per day) that mention other Twitter users to measure the communication level with other users. Models 1 to 3 each incorporate these alternative Twitter variables. Given the high correlation between *Tweets* and *Mention others* (see the correlation matrix at the bottom of this table), we do not include all three alternatives together. Instead, we include *Tweets* and *Re-tweets* (Model 4) and *Re-tweets* and *Mention others* (Model 5). The dependent variable is the ICO fundraising amount (natural logarithm). The main independent variable of interest is *Confidence*, which is based on the average value of the ratings from mTurk participants who evaluate the overall confidence of the team based purely on the team picture. The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias. Variable definitions are in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Confidence	1.550**	1.440**	1.556**	1.443**	1.445**
	(2.403)	(2.230)	(2.408)	(2.232)	(2.234)
Team size	0.548***	0.550***	0.551***	0.544***	0.547***
	(6.139)	(6.152)	(6.179)	(6.066)	(6.098)
Team size squared	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-3.954)	(-3.962)	(-3.990)	(-3.886)	(-3.915)
Member names	-6.960	-6.821	-6.890	-6.970	-6.910
	(-0.753)	(-0.727)	(-0.746)	(-0.742)	(-0.736)
Pre-sale	0.207	0.301	0.207	0.291	0.292
	(0.311)	(0.449)	(0.310)	(0.435)	(0.436)
Hardcap_ln	0.033	0.067	0.034	0.062	0.064
	(0.133)	(0.268)	(0.138)	(0.249)	(0.255)
Offered ownership	-2.042	-2.321	-2.095	-2.180	-2.229
	(-1.265)	(-1.446)	(-1.297)	(-1.345)	(-1.375)
Offered tokens	0.112**	0.109**	0.113**	0.108**	0.109**
	(2.279)	(2.225)	(2.287)	(2.220)	(2.225)
Ethereum	0.755	0.770	0.759	0.756	0.759
	(0.790)	(0.805)	(0.793)	(0.791)	(0.793)
Tweets	0.022*	-	-	0.018*	-
	(1.663)	-	-	(1.884)	-
Re-tweets	-	1.163**	-	1.122**	1.143**
	-	(2.178)	-	(2.093)	(2.131)
Mention others	-	-	0.015**	-	0.012**
	-	-	(2.140)	-	(2.566)
Female percentage	-7.914***	-8.205***	-7.939***	-8.142***	-8.169***
	(-2.903)	(-3.008)	(-2.911)	(-2.981)	(-2.990)

Location	0.007	-0.060	-0.002	-0.036	-0.045
	(0.011)	(-0.096)	(-0.003)	(-0.059)	(-0.072)
Trend effect	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(-3.543)	(-3.455)	(-3.570)	(-3.401)	(-3.422)
Constant	11.468	10.756	11.415	10.905	10.848
	(1.139)	(1.054)	(1.134)	(1.069)	(1.063)
Observations	515	515	515	515	515
Adjusted R-squared	0.171	0.177	0.170	0.177	0.176
Correlation matrix:					
	a	b	c		
a Tweets	1	-	-		
b Re-tweets	0.0857	1	-		
c Mention others	0.9942	0.0602			

Appendix A.

Amount raised (in million USD)	The amount of funding raised through an ICO. Source: Icobench.com.
Amount raised	The natural logarithm of (the amount of funding raised +1) by the ICO (in USD). The addition of one is to include zero funds raised. Source: Icobench.com.
Main independent variable:	
Confidence	The average value of the ratings from mTurk participants who evaluate the overall confidence of the team based purely on the team picture. The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias.
Control variables:	
Team size	The number of team members. Source: Icobench.com, ICO venture websites, and white papers.
Team size squared	The number of team members squared. Source: Icobench.com, ICO venture websites, and white papers.
Member names	The percentage of having full names for team members. Source: Icobench.com, ICO venture websites, and white papers.
Pre-sale	A dummy variable coded one if there is a pre-sale and zero otherwise. Source: Icobench.com.
Hardcap_ln	A natural logarithm of the hard cap (in US dollars) of an ICO. We collect data on the hard cap amount from Icobench.com. When the hard cap amount is in the token currency, we convert it into US dollars using the exchange rate on the last available day from Coinmarketcap.com.
Offered ownership	The percentage of tokens distributed to token holders in the ICO relative to all the tokens created. Source: Icobench.com and white papers.
Offered tokens	The natural logarithm of the number of tokens to be issued. Source: Icobench.com and white papers.
Ethereum	A dummy variable coded one if the token is based on an Ethereum-based platform and zero otherwise. Source: Icobench.com.
Twitter	The activity level on Twitter measured at the beginning of each offering, valued from [0, 1, 2, 3], where low values stand for low activity. Source: Icobench.com.
Female percentage	The percentage of female members in a team picture (collected from Icobench.com).
Location	A dummy variable coded one if the ICO is in the top five countries (United States, United Kingdom, Singapore, Russia, and Estonia) ranked by the total fundraising amount per country and zero otherwise. The ranking result is the same as sorted by the total number of ICOs per country. Source: Icobench.com.

Trend effect	A count variable coded one for the first ICO in our sample set, two for the second ICO, and so on.
Other team visual characteristics:	
Attractiveness	The average value of the ratings from mTurk participants who evaluate the overall attractiveness of the team based purely on the team picture (collected from Icobench.com). The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias.
Intelligence	The average value of the ratings from mTurk participants who evaluate the overall intelligence of the team based purely on the team picture (collected from Icobench.com). The rating scale is from 1 (weak) to 5 (strong) and each participant's ratings are z-score-normalized to account for positivity or negativity bias.
Instrumental variables:	
Relative age	The difference in the birthdate of CEOs relative to school entry cut-off dates.
Mimicking behavior	For each ICO, we compute the average level of confidence in the ICOs in the same industry over the previous quarter.
Other controls for robustness:	
Campaign duration	The ICO campaign period in days, calculated from the ICO start date to the ICO end date. Source: Icobench.com
White paper	A dummy variable coded one if an ICO project provides a valid link to the white paper on their Icobench webpage and zero otherwise. We cross-check the ICO venture websites to confirm the link is valid. This variable measures whether it is convenient for investors to locate the white paper quickly compared with conducting additional research (e.g., checking external websites). Data are from Icobench and ICO venture websites.
Bitcoin (in 1,000 USD)	We collect the Bitcoin price data from Coinmarketcap.com.
Visual feature variables:	
Glasses percentage	The percentage of team members wearing glasses in a team picture (collected from Icobench.com).
Suit percentage	The percentage of team members wearing a suit in a team picture (collected from Icobench.com).
Smiling percentage	The percentage of team members smiling in a team picture (collected from Icobench.com).
Face proportion	The proportion of face area in a team image (collected from Icobench.com). The higher the face proportion, the closer people are to the camera.
Crossed arms	A dummy value coded one if at least one member is showing the "arms crossed" pose in the team picture (collected from Icobench.com) and zero otherwise.

Same place	A dummy value coded one if at least two of the team member images (collected from Icobench.com) are taken in the same place and zero otherwise.
Same clothes	A dummy value coded one if at least two of the team members are wearing the same team clothes in a team picture (collected from Icobench.com) and zero otherwise.
Uniform background	A dummy variable coded one if the background of the team picture (collected from Icobench.com) is uniform.
Black and white image	A dummy value coded one if the whole team picture (collected from Icobench.com) is black and white and zero otherwise.
Alternative variables for Tweet activity:	
Tweets	Average number of tweets (per day) over the campaign period to measure the overall activity level of the ICO's Twitter content (collected from each venture's Twitter account).
Re-tweets	Average number of re-tweets (per day) over the campaign period to measure the interaction level with other users' Twitter content (collected from each venture's Twitter account).
Mention others	Average number of tweets (per day) that mention other Twitter users to measure the communication level with other users (collected from each venture's Twitter account).