Angel Investment and First Impressions*

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Abstract

We examine the role of first impressions in angel investor decision-making. Video stills of entrepreneurs pitching on the Shark Tank show and in Startup Battlefield competitions yield six measures of first impressions of entrepreneurs' facial traits and two principal components: one that captures general ability and the other that contrasts charm and managerial ability. We find positive associations between both components and the likelihood of entrepreneurs receiving an investment offer or winning a competition round. Post-event business outcome analyses reveal that investors internalize entrepreneurs' general ability rationally but exhibit irrational tendencies when internalizing entrepreneurs' charm and managerial ability. Investment experience mitigates investors' irrational use of charm and managerial ability cues.

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1. Introduction

The tremendous growth of angel investment and venture capital (VC) investment over the past two decades (Chemmanur and Fulghieri, 2014; Gornall and Strebulaev, 2015) calls for a deeper understanding of the early stage startup investment decision process. Such investment decisions face a great deal of information asymmetry (Hochberg, Serrano, and Ziedonis, 2018; Howell, 2020). They often take place during, or immediately following, face-to-face interactions between early stage investors and entrepreneurs pitching startup businesses. With limited information available about the business, early stage investors may be betting on the entrepreneur, rather than only on the business idea. Other settings, ranging from IPO pricing to political elections (Blankespoor, Hendricks, and Miller, 2017; Todorov et al., 2005), suggest that first impressions may contain useful information and reduce the information asymmetry for early stage investors.

In this study, we focus on the role that first impressions conveyed through entrepreneurs' facial traits play in early stage investors' decision-making. Neurological research shows that first impressions are formed swiftly and, once formed, continue to influence decision-making (Schiller et al., 2009). Facial traits are related to various outcomes in the labor and capital markets, including workers' wages (Hamermesh and Biddle, 1994), CEO performance and selection (Rule and Ambady, 2008; Graham, Harvey, and Puri, 2017), IPO pricing (Blankespoor, Hendricks, and Miller, 2017), analyst job performance (Cao et al., 2020), and peer-to-peer lending (Duarte, Siegel, and Young, 2012). We focus on first impressions concerning six facial traits extracted from the psychology, finance, management, and entrepreneurship literatures: competence, confidence, trustworthiness, the ability to handle pressure, physical attractiveness, and likability.[1]

[1] These six facial traits are prevalent in the psychology literature (e.g., Hehman et al., 2017; Stolier et al., 2018). They are also featured in the studies that employ surveys to elicit the entrepreneurs' characteristics that angel investors and venture capitalists find desirable for purposes of investment selection (Macmillan, Siegel, and Subbanarasimha, 1985;

We exploit two real-life settings in which entrepreneurs pitch to angel investors: the Shark Tank television show and TechCrunch Startup Battlefield competitions. In the Shark Tank setting, entrepreneurs appear on a national television show to pitch their businesses to the sharks, a group of well-established angel investors. Each investor then decides whether to invest in the pitched businesses and, if so, negotiates the investment terms. Investors are paid to participate in the show, but they invest their own money in the entrepreneurs' businesses. In the Startup Battlefield competition setting, a group of judges (mostly angel investors, venture capitalists, or successful entrepreneurs) hear early stage startup pitches in front of a live audience, after which they collectively decide competition winners in private deliberations. The competition offers an equity-free cash prize, but the judges do not invest their own money into the startups they are judging during the competition. Both settings allow us to observe angel investors' decisions after hearing and discussing the entrepreneurs' actual pitches.

Because we cannot directly measure the angel investors' first impressions, we recruit U.S. survey respondents to rate the entrepreneurs' video stills along the six facial traits of interest. To the extent that humans form first impressions similarly (particularly if they come from similar cultural contexts), the angel investors' first impressions are likely to be similar to those of our survey respondents.[2] Consistent with the findings from Graham, Harvey, and Puri (2017) and Blankespoor, Hendricks, and Miller (2017), many of the first impressions of the six facial traits are highly correlated. Similar to Kaplan, Klebanov, and Sorensen (2012) and Kaplan and Sorensen

Macmillan, Zemann, and Subbanarasimha, 1987; Gompers et al., 2020), the literature exploring the characteristics of successful CEOs (Kaplan, Klebanov, and Sorensen, 2012; Blankespoor, Hendricks, and Miller, 2017; Graham, Harvey, and Puri, 2017; Kaplan and Sorensen, 2021), the studies concerning transformational leadership and entrepreneurship (Judge and Bono, 2000; Brandstatter, 2011; Berge et al., 2015), and the literature focusing on business creation and success (Zhao and Seibert, 2006; Kerr, Kerr, and Xu, 2017; Chadwick and Raver, 2020).

[2] Several research studies report a remarkable agreement across individuals in judgments based on first impressions regarding a variety of facial traits (Kalick et al., 1998; Willis and Todorov, 2006; Zebrowitz, Bronstad, and Lee, 2007; Carré, McCormick, and Mondloch, 2009; Olivola and Todorov, 2010; Zebrowitz and Montepare, 2015).

(2021), we use principal component analysis to condense the dimensionality of the six facial traits into two principal components.

The first principal component (*gen*) loads positively on all six traits. Similar to Kaplan, Klebanov, and Klebanov (2012) and Kaplan and Sorensen (2021), we interpret *gen* as a measure of perceived general ability. The second principal component (*cvm*) loads positively on attractiveness and likability, which we interpret as the collection of traits associated with charm, and loads negatively on capability, confidence, and ability to handle stress, which we interpret as the collection of traits associated with managerial ability. By construction, these two components not only explain a large fraction of the overall variability of the measures of the facial traits but are also orthogonal.

We compare the loadings for the two principal components between the Shark Tank sample and the Startup Battlefield sample. Although the principal component analysis is applied to distinct pools of survey respondents who rated entrepreneurs from the two distinct settings, the loadings for the two principal components are nearly the same. The evidence supports the notion that there is a common component in individual's judgements based on first impressions of facial traits, justifying our survey-based approach to proxying for the angel investors' first impressions. We use these two condensed measures to analyze the role that first impressions of entrepreneurs' facial traits play in angel investors' decision-making and in entrepreneurs' future business outcomes.

In our first analysis, we relate the probability of winning, that is, receiving an investment offer on a Shark Tank show or winning a competition round in a Startup Battlefield competition, to first impressions of entrepreneurs' facial traits, other entrepreneur characteristics, business characteristics, and a range of fixed effects. We find that regression coefficients associated with both general ability (*gen*) and charm versus managerial ability (*cvm*) principal components are positive, suggesting that angel investors/competition judges value general ability and, on the margin, entrepreneurs' charm over their managerial ability.

Next, we evaluate how entrepreneurs' business outcomes relate to the first impressions they convey through facial traits. Extant literature offers evidence of both rational and behavioral use of first impressions. For example, consistent with a rational interpretation, Halford and Hsu (2020) report that CEOs viewed as more attractive are associated with better stock returns surrounding their job announcements and around earnings announcements. On the other hand, Graham, Harvey, and Puri (2017) find no evidence that CEO performance is related to first impressions of competence or attractiveness, suggesting a behavioral explanation for corporate boards' preference for selecting more competent-looking and more attractive CEO candidates, and offering them higher pay.

Collecting data from various sources, we define an ordinal variable with three categories to measure the level of business outcome*:* *Home Run* (indicating the most successful ventures), *Operating* (indicating other ventures still in business), and *Failure* (indicating ventures that failed within three years of appearing on the Shark Tank show or participating in a Startup Battlefield competition). We relate this measure of business outcome to first impressions of entrepreneurs' facial traits, other entrepreneur characteristics, business characteristics, and a range of fixed effects. We find that entrepreneurs' general ability is positively associated with future success, whereas businesses pitched by entrepreneurs who show more charm than managerial ability are negatively associated with future success. Therefore, angel investors appear to incorporate first impressions of entrepreneurs' general ability in a rational manner, but their use of first impressions of charm versus managerial ability appears irrational. Indeed, whereas angel investors/competition judges value charm over managerial ability when making decisions regarding investment offers/competition winners, the association between business outcome and the second principal component of entrepreneurs' facial traits is negative. This evidence suggests that what ultimately matters is managerial ability, not charm. This pattern highlights a nuanced interpretation of the role of first impressions. Usually, a study either advances rational explanations (e.g., Halford and Hsu, 2020) or offers behavioral explanations (e.g., Graham, Harvey, and Puri, 2017). Our paper presents novel evidence that economic agents, in this instance angel investors, can both rationally internalize some visual cues—first impressions of general ability—and irrationally internalize others—first impressions of charm versus managerial ability.

Our final inquiry is whether angel investors improve their individual decision-making as they gain more experience, as suggested by classical learning-by-doing models (Arrow, 1962; Grossman, Kihlstrom, and Mirman, 1977). The Startup Battlefield setting is not well-suited to answer this question because the judges reach decisions jointly. In the Shark Tank setting, however, the decision-making regarding whether to invest is in the hands of individual investors. Over time, investors eventually garner more experience by participating in tens, even hundreds of pitches. Moreover, they begin appearing on the show at different points in time. Therefore, the Shark Tank sample offers a unique opportunity for additional insights into whether experience affects angel investors' decision-making. We study angel investors' learning-by-doing by considering the experience of each investor, measured as the number of pitches that the investor had previously heard. We find that investors' experience mitigates their irrational tendency to internalize entrepreneurs' charm versus managerial ability in their decisions.

Our paper provides multiple contributions to the literature. First, we extend prior research regarding the factors related to early stage investment selection (Gompers et al., 2020; Howell 2020) by considering the information contained in the first impressions of entrepreneurs' facial traits. Our analyses of the Shark Tank and Startup Battlefield settings show that first impressions of entrepreneurs' facial traits play a role in early stage investment decision-making.

Second, we find *both* rational and irrational aspects of angel investors' decision-making. Our evidence shows that angel investors incorporate first impressions of entrepreneurs' general ability in a manner consistent with rational behavior. At the same time, angel investors exhibit behavioral tendencies. They subscribe to a variant of the beauty premium (Hamermesh and Biddle, 1994), rewarding charm (over managerial ability) despite its negative association with entrepreneurs' future success.

Third, our paper highlights the role of learning-by-doing in improving the quality of angel investors' investment selection, and expands our understanding of the role of learning in the decision-making of various economic agents,[3] especially during the entrepreneurial investment process. In our context, we show that angel investors' irrational tendency to reward charm over managerial ability is mitigated as investors gain decision-making experience.

2. Related research

Economists have long utilized various TV shows to draw inferences concerning human decision-making (e.g., Gertner, 1993; Metrick, 1995; Berk, Hughson, and Vandezande, 1996; Levitt, 2004; Post et al., 2008). Whereas Shark Tank is a TV show with an inevitable element of entertainment, what we are measuring—the role of first impressions of entrepreneurs conveyed through visual cues—is likely relevant across a range of real-life entrepreneurial investment situations. Also, because angel investors tend to participate in multiple seasons of the Shark Tank show, we harness that opportunity to evaluate the role that angel investors' experience may play in their decision-making.

[3] See, for example, Mikhail, Walther, and Williams (1997), Feng and Seasholes (2005), Seru, Shumway, and Stoffman (2010), Chiang et al., (2011), Kempf, Manconi, and Spalt (2017), and Howell (2021).

Our use of Startup Battlefield competitions follows in the footsteps of recent studies that use pitch competitions to understand entrepreneurs' behavior or venture capital financing decisions (Brooks et al., 2014; Howell, 2020; Howell, 2021). The Startup Battlefield setting allows us to explore the role of the same visual cues as in Shark Tank, but without as much of an entertainment element. The trade-off is that Startup Battlefield judges do not make investment decisions during the competition; rather, they collectively decide competition round winners (and, in later stages, overall competition winners and runners-up) in private deliberations. The two similar settings, Shark Tank and Startup Battlefield, enable us to capture factors that may be common in angel investors' decision-making, helping us enhance the generalizability of our findings regarding the role of first impressions that entrepreneurs convey through facial traits.

Our paper relates to recent studies that exploit new data sources to study early stage investors' decision-making. Boulton, Shohfi, and Zhu (2019) used Shark Tank to study the effect of entrepreneurs' demographic characteristics such as gender, race, age, and education—not including first impressions—on the likelihood of receiving offers, entrepreneurs' asking valuations, and investors' valuations.[4] Bernstein, Korteweg, and Laws (2017) conduct experiments with randomized investor information sets on AngelList to study how investor decisions are associated with different kinds of information (e.g., founding team, startup traction, current investor identity). Howell (2020, 2021) uses proprietary data from new venture competitions to study the role of competitions in reducing the magnitude of information frictions faced by venture capital (Howell, 2020) and the way entrepreneurs respond to negative feedback about their venture quality (Howell, 2021). Brooks et al. (2014) use a sample from pitch competitions to study the

[4] Boulton, Shohfi, and Zhu (2019) did not set out to study the role of first impressions in the Shark Tank context. Therefore, their specifications do not feature any covariates related to first impressions. Nonetheless, their results regarding the roles of gender and entrepreneurial team structure (solo contestants versus teams) in the context of receiving offers are consistent with our findings.

relation between winning the competition and contestants' gender and physical attractiveness. However, they evaluate neither the relation between competition judges' decision-making and the subsequent business outcomes nor the role of learning-by-doing in mitigating the competition judges' behavioral biases.[5]

In contrast to our focus on the information imparted at the very beginning of a face-to-face pitch (*first impressions* of entrepreneurs' facial traits), Hu and Ma (2021) study the effect of persuasive communication by using machine-learning algorithms to quantify visual, vocal, and verbal features throughout pre-recorded pitch videos. They find that pitch positivity (passionate, warm delivery) is positively associated with funding probability, but, conditional on funding, higher pitch positivity predicts startup underperformance. By comparison, we exploit a survey approach to measure directly human perception of entrepreneurs. Our finding that the principal component analysis of two distinct samples yields almost identical component loadings not only demonstrates reproducibility, but it also lends support for the premise we share with the machine learning approach—that there is a common component or systematic pattern in human perception. Unlike Hu and Ma (2021), we also study whether investor experience, learning-by-doing, helps mitigate angel investors' behavioral biases.

[5] Brooks et al. (2014) focus on gender imbalance in entrepreneurship. They document a consistent gender gap in entrepreneurial persuasiveness: investors appear to prefer pitches presented by male entrepreneurs to those presented by female entrepreneurs (neither Boulton, Shohfi, and Zhu (2019) nor this paper find any evidence of a gender gap). Brooks et al. (2014) further report that the gender gap they find is moderated by male physical attractiveness: physical attractiveness incrementally enhances the persuasiveness of the pitches delivered by male entrepreneurs (but not of the pitches delivered by female entrepreneurs).

3. Description of the settings

3.1 The Shark Tank TV show

Shark Tank is an American reality television show. It features a panel of five angel investors called the sharks. The angel investors hear business pitches from entrepreneurs on the show, ask questions, offer comments, and decide whether to extend an investment offer to the entrepreneurs. If all investors opt out, the entrepreneur (an individual or a team) leaves without a deal. If any of the investors expresses an interest, further discussions ensue between the investors and the entrepreneur(s), as well as among the investors. Discussions range widely from inquiries about past sales, sales projections, and production issues, to details concerning financing and the terms of the investment offers. It is a *de facto* negotiation process that may lead to a deal between the entrepreneur(s) and one or more investors. Whereas the investors are paid for being on the show, if they fund a business, they commit their own money and, if applicable, other resources (such as distribution channels). Each aired pitch lasts about 10-12 minutes. The recording of the full pitch and the subsequent discussions is edited to fit the allotted airtime. Not every recorded pitch is ultimately aired; the selection of pitches to be aired is based on perceived entertainment value.

3.2 The Startup Battlefield competitions

TechCrunch, an online newspaper focusing on technology and startups, hosts annual Disrupt conferences around the globe. Each conference includes a Startup Battlefield competition in which early stage startup entrepreneurs present their businesses to a group of judges on stage. The stated goal of the Startup Battlefield competitions is to identify the most disruptive business ideas in technology; there is less emphasis on entertainment value than in Shark Tank. The Startup Battlefield competitions are informative about the decision-making of early stage investors because the majority of the judges are angel investors, venture capitalists, or successful entrepreneurs. Video recordings of most competitions are available online. The format of Startup Battlefield competitions, each featuring up to two dozen startups competing over a two-day period, relies on running time-efficient pitches. Each pitch lasts about 12 minutes, starting with about six minutes for the startup entrepreneurs' uninterrupted presentation, followed by about six minutes of answering the judges' questions. The resulting video recordings are unedited. Unlike Shark Tank investors, Startup Battlefield judges do not make any investment financing deals with the entrepreneurs on stage; rather, they merely judge the competition and pick winners.

4. Data and Summary Statistics

Our Shark Tank data features all 379 pitches aired during the first five seasons. Our Startup Battlefield data collection starts with the list of contestants downloaded from TechCrunch's website for Startup Battlefield competitions hosted in New York, San Francisco, Berlin, and London between 2013 and 2019. We use product names and the keywords "Disrupt" and "Startup Battlefield" to search for video recordings of the pitches within TechCrunch's website and on YouTube. Our Startup Battlefield sample includes all the pitches with video recordings from which we could extract video stills with reasonable image resolutions and with available *LinkedIn* profiles for the entrepreneurs, yielding a total of 352 pitches.

Video Stills. For each Shark Tank and Startup Battlefield pitch, we take standardized video stills of the entrepreneurs and use the stills to gather survey responses regarding first impressions of the entrepreneurs' facial traits (see Section 5 for details).

Entrepreneur characteristics. We collect entrepreneur characteristics from two sources. First, we code the gender of the main presenter and the team/solo format from watching the video recordings. Second, we search on *LinkedIn* to collect information regarding the entrepreneurs' educational and professional experiences. We capture the highest level of education the entrepreneurs attained by three categories—graduate/professional degree, bachelor's degree, and below college. The entrepreneurs' professional background is also coded into three categories: Executive (e.g., CEO, Managing Director), Professional (e.g., engineer, lawyer, doctor, financial analyst, or a lower-level leadership role), and Other. For the pitches delivered by a team, we set the level of education and professional background to the highest level achieved across the team members. Finally, we measure entrepreneurs' performance during the pitch by extracting from the video recordings an indicator variable, *Calculation Error*. It reflects whether the entrepreneur/team made a noticeable calculation error during the pitch or subsequent interaction with angel investors.[6]

Panel A of Table 1 summarizes Shark Tank entrepreneur characteristics. Among the 379 pitches, 224 (59%) are delivered by a solo entrepreneur, while the remaining 155 (41%) are delivered by a team of entrepreneurs. In addition, 97 (26%) pitches are delivered by a solo female entrepreneur or by an all-female team. In terms of educational background, 66 (17%) pitches are given by entrepreneurs with graduate/professional education, 142 (37%) by entrepreneurs with a bachelor's degree, and 171 (45%) by entrepreneurs with educational levels below college. As for prior experience, 115 (30%) pitches are given by entrepreneurs with executive experience, 69 (18%) by entrepreneurs with professional experience, and 195 (52%) by entrepreneurs with other experience. During the show, 60 (16%) entrepreneurs/teams make a noticeable calculation error during their pitch or subsequent discussion with investors.

Panel A of Table 2 summarizes Startup Battlefield entrepreneur characteristics. Similar to the Shark Tank sample, the entrepreneurs participating in the Startup Battlefield competitions are

[6] The challenge in pursuing such a measure is identifying a salient characteristic that matters for the shark investors' or competition judges' judgment and that can be reliably and uniformly measured across a large and heterogeneous set of pitches and subsequent discussions. *Calculation Error* is a somewhat crude proxy for underperformance during the pitch. Nonetheless, its distinct advantage is that it was clearly noticeable during the pitch.

predominantly male, with female entrepreneurs accounting for 19%. Perhaps because of its focus on the technology sector, Startup Battlefield competitions attract more highly educated entrepreneurs, with more than one-half (54%) of the competing entrepreneurs holding advanced graduate or professional degrees, relative to 17% in the Shark Tank sample. Perhaps relatedly, only six of 352 entrepreneurs/teams (2%) made a noticeable calculation error during their pitch or during the subsequent stage of providing answers to competition judges.

Business characteristics. At the beginning of their presentations, Shark Tank entrepreneurs state the amount of cash they request in exchange for a certain percentage of the equity of their businesses (all asking terms have an equity-only structure). We record the entrepreneurs' asking terms and the corresponding equity shares given up. As the entrepreneurs introduce their businesses, we collect information on the type of products or services they sell, their patent status, and the stage of their businesses. Based on the description the entrepreneurs provide during the pitch and a subsequent online search, we assign each business to an industry. Panel A in Internet Appendix Table A1 contains examples of businesses assigned to each industry. We discern the patent status (if revealed) and express it through indicator variables *Approved*, *Rejected*, and *Pending*. We also extract the stage of the pitched business (if revealed) and code it through indicator variables *Early*, *Growth*, and *Expansion*.

Panel B of Table 1 shows that the average (median) asking cash amount is 246 (150) thousand dollars. The sample contains some relatively smaller scale businesses, but it also contains businesses that the entrepreneurs valued at thirty million dollars. The average (median) equity the entrepreneurs are willing to relinquish is 18.63% (20.00%). The entrepreneurs' average (median) implied firm valuation is 1.881 million (850 thousand) dollars. Of the 379 businesses, 128 (34%) had their patent information revealed on the show; 80 (21%) businesses already had the patent approved. Finally, the products pitched on the show range across a wide spectrum of industries, with the largest presence of products from the Food and Clothes & Accessories industries (17% and 13%, respectively). Internet Appendix Table A2, Panel A shows the industry distribution of the Shark Tank sample.

The Startup Battlefield business characteristics we collect include the business description, industry classification, date of founding (to estimate the business stage at the time of the competition), and the number of patents. A paid Crunchbase Pro account subscription enabled us to gather details about the number of funding rounds, as well as the date and the dollar amount for each round of funding. Using the event dates of each Startup Battlefield competition and the announcement dates of funding rounds, we calculate the funding each startup raised before participating in the competition. Crunchbase does not offer information about past sales or the entrepreneurs' own investment in their businesses. Identifying the correct business is perhaps the most challenging part of the process because there are often multiple businesses with the same product name listed on Crunchbase or there are name changes after a startup participates in a Startup Battlefield competition. We ensure proper identification by matching the startup not only by its product name but also by the startup's founders listed on Crunchbase.

Panel B of Table 2 shows the summary statistics of the businesses participating in Startup Battlefield competitions. They are heavily concentrated in technology-related categories, with 63% from the software industry. Internet Appendix Table A2, Panel B shows the industry distribution of the Startup Battlefield sample. The majority of these startups (84%) are in the early stage; they were founded less than three years before appearing in a Startup Battlefield competition.[7] A fraction of the startups have an approved patent (22%).[8] The median for the funds raised before the competition is zero, suggesting that at least one-half of the startups did not raise external funding before their Startup Battlefield competition appearance.

Investor decision-making. Following the Shark Tank entrepreneurs' presentations and a period of discussion, investors decide whether to make an offer or opt out. They may make one or more offers, by themselves or teaming up with other investors, and revise the terms of the offers (including which investors participate in those offers). We record for every pitched business each investor's decision regarding making an offer, and the number of offers the entrepreneurs receive.

Panel C of Table 1 summarizes the frequency distribution of investor offers by pitched business. Of the 379 pitched businesses, 152 (40%) did not receive any offers, whereas 227 (60%) received one or more offers. At the investor-pitch level, there are 1,895 observations (379 pitches heard by five investors each). An investor made an offer in 492 (25.96%) of the 1,895 observations.

The Startup Battlefield competition format does not feature the entrepreneurs' asking terms because the startups are pitching to win an equity-free cash prize. Each round of a Startup Battlefield competition features a panel of judges who evaluate the startups and select the competition round winner. Competition round winners proceed to the final round, in which a newly assembled panel of judges selects the runner-up and the overall competition winner. Although the judges do not invest their own money in the winning startup on the spot, their decisions regarding competition round winners reflect their perceived value of the startups in a manner akin to the investment decisions on Shark Tank. Panel C of Table 2 reports the breakdown of the competing

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[7] According to the TechCrunch website (https://techcrunch.com/startup-battlefield/faq/), good candidates for appearing in a Startup Battlefield competition are "… companies that are bootstrapped, Pre-Seed, Seed, or Series A. The ideal fit for Startup Battlefield has had minimal press coverage, and is going to showcase something disruptive on stage."

[8] The number of patents owned by the startups at the time of the competition is not available. To keep the control variables comparable to those from our Shark Tank setting, we use current patent data (collected from Crunchbase) as a proxy. Reassuringly, the results are similar with or without the controls for patent status (untabulated).

Startup Battlefield entrepreneurs by the judges' decisions. Judges selected 86 (24.43%) competition round winners from the 352 startups.

Business outcomes. To characterize the future success of the businesses that appeared on Shark Tank or participated in a Startup Battlefield competition, we follow the businesses and code the outcome into three broad categories: *Home Run*, *Operating*, and *Failure*. The *Home Run* category encapsulates the most successful businesses. We aim to capture the right-tail successes (Howell, 2020), the very successful outcomes typically regarded as crucial for the investment decisions of angel investors and venture capitalists. The remaining businesses are classified as *Operating* (indicating ventures still in business) or as *Failure*. Similar to Ewens and Townsend (2020) and Hu and Ma (2021), we classify a business as a failure if its company website became inactive within three years since its appearance on Shark Tank or a Startup Battlefield competition or if its social media explicitly mentioned that the company had gone out of business.

To identify Shark Tank home runs, we search extensively over a range of online platforms such as Associated Press News, CNBC, Forbes, Fortune, and USA Today, and record the information concerning Shark Tank businesses' revenues and significant acquisitions (Ewens and Townsend, 2020).[9] We classify the Shark Tank startups as *Home Run* if they satisfy either one of the two conditions as of 2019: the revenue is greater than $10 million, or the startup was acquired for more than $10 million (more than five times the entrepreneurs' average asking valuation of $1.88 million). The list of the home runs in our Shark Tank sample and the information sources are provided in Internet Appendix Table A3, Panel A.

[9] Whereas it provides comprehensive coverage of startups that appear on the Startup Battlefield competitions, Crunchbase is not a fruitful forum for collecting information regarding potential home runs for Shark Tank startups because only 32.7% of our Shark Tank startups appear in Crunchbase. However, the popularity of the Shark Tank show made it possible to gather information from media coverage.

Startups that participated in the Startup Battlefield competitions do not garner similar media popularity as those appearing on the Shark Tank show. Therefore, gathering the same information to define home runs similarly for the Startup Battlefield sample is not feasible. Instead, we identify Startup Battlefield home runs from the information available in Crunchbase, including the number of employees (Puri and Zarutskie, 2012; Adelino, Ma, and Robinson, 2017; Howell, 2020; Howell, 2021; Hu and Ma, 2021), revenues, significant acquisitions (Ewens and Townsend, 2020), and post-event funding raised (Ewens and Townsend, 2020; Hu and Ma, 2021). Specifically, we classify the Startup Battlefield startups as *Home Run* if they satisfy at least one of the following three conditions: the number of employees is greater than 500, the revenue is greater than \$50 million, or the amount of raised funding is in the top 2% of the sample. The list of Startup Battlefield home runs is provided in Internet Appendix Table A3, Panel B.

Panel D of Table 1 presents the classification of the 379 businesses featured on the Shark Tank show during its first five seasons. Of these, 26 (7%) are classified as home run businesses (*Home Run*), 257 (68%) businesses continued to operate for at least three years (*Operating*) after their appearance on the Shark Tank show (although they did not rise to the stature of a home run), and 96 (25%) businesses failed (*Failure*). Panel D of Table 2 shows that 12 of the 352 Startup Battlefield startups are classified as *Home Run* (3%), 297 as *Operating* (85%), and 43 (12%) as *Failure*.

< Table 1 about here >

< Table 2 about here >

5. First Impression Measures of Entrepreneurs' Facial Traits

5.1. First impressions

First impressions are formed rapidly[10] by intense activity in the amygdala and the posterior cingulate cortex (PCC), primitive parts of the human brain (Schiller et al., 2009). Functional magnetic resonance imaging (fMRI) studies show that the amygdala, among others, is involved in the formation of first impressions of trustworthiness (Engell, Haxby, and Todorov, 2007; Winston et al., 2002) and assessments of emotion from facial expressions and body movements (Adolphs, 2002; Adolphs and Baron-Cohen, 2002; Hadjikhani and Gelder, 2003). Following their formation, first impressions contribute strongly to decision-making in various settings (e.g., Blankespoor, Hendricks, and Miller, 2017; Todorov et al., 2005). We extend the literature by studying the extent and nature of the role that first impressions conveyed through facial traits play in the angel investment setting.

Because we cannot directly observe the angel investors' first impressions of the Shark Tank and Startup Battlefield entrepreneurs' facial traits, we instead survey U.S. respondents and measure their first impressions of the entrepreneurs' facial traits from video stills. Although perceivers' characteristics may guide how they gather impressions of others (Hehman et al., 2017), the psychology literature consistently documents a remarkable agreement across individuals in judgments based on first impressions regarding a variety of facial traits, including aggressiveness, competence, health, and trustworthiness (e.g., Kalick et al., 1998; Willis and Todorov, 2006; Zebrowitz, Bronstad, and Lee, 2007; Carré, McCormick, and Mondloch, 2009; Olivola and Todorov, 2010; Zebrowitz and Montepare, 2015). To the degree that humans form first impressions similarly (particularly if they come from similar cultural contexts), the survey

[10] Willis and Todorov (2006) find that people make trait inferences from facial appearance in 100 milliseconds.

respondents' first impressions are likely to be correlated to those formed by the angel investors and, therefore, likely to be informative.

Psychology studies exploring the role of first impressions based on facial traits have identified one to two dozen traits.[11] To strike a balance between the total number of entrepreneurs' facial traits that each respondent would need to evaluate and the quality of their evaluations, we sought to limit the number of facial traits to those that the literature suggests are the most germane in our context. We conducted an extensive review, considering the surveys that elicit the entrepreneurs' characteristics that angel investors and venture capitalists find desirable for purposes of investment selection (Macmillan, Siegel, and Subbanarasimha, 1985; Macmillan, Zemann, and Subbanarasimha, 1987; Gompers et al., 2020), the literature exploring the characteristics of successful CEOs (Kaplan, Klebanov, and Sorensen, 2012; Blankespoor, Hendricks, and Miller, 2017; Graham, Harvey, and Puri, 2017; Kaplan and Sorensen, 2021), and the studies that focus on transformational leadership, entrepreneurship, and business creation and success (Judge and Bono, 2000; Zhao and Seibert, 2006; Brandstatter, 2011; Berge et al., 2015; Kerr, Kerr, and Xu, 2017; Chadwick and Raver, 2020).

Our literature review yielded six facial traits: competence, confidence, trustworthiness, ability to handle pressure, attractiveness, and likability. Four of the six—attractiveness, competence, trustworthiness, and likability—coincide with those used in Graham, Harvey, and Puri (2017). The remaining two facial traits—confidence and the ability to handle pressure—capture the reality that entrepreneurs frequently operate in highly dynamic environments and experience intense levels of competition and stress. They are documented in the literature as key components of transformational leadership and entrepreneurship (Judge and Bono, 2000; Brandstatter, 2011;

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[11] For example, Oosterhof and Todorov (2008) and Stolier et al. (2018) recognize 13 traits, whereas Hehman et al. (2017) recognize as many as 23.

Berge et al., 2015), and essential personality traits that matter for business creation and success (Zhao and Seibert, 2006; Kerr, Kerr, and Xu, 2017; Chadwick and Raver, 2020).

Research in economics and finance has examined the effect of first impression measures in the labor market and the capital markets.[12] For example, Blankespoor, Hendricks, and Miller (2017) study the relation between perceptions of CEOs' characteristics (competence, attractiveness, and trustworthiness) and firm valuation in the IPO setting. They report that perceptions of both the attractiveness and the competence of the CEOs are positively associated with the IPO firm value. Graham, Harvey, and Puri (2017) investigate the role of CEOs' attractiveness, competence, trustworthiness, and likability on the board of directors' decision to select a new CEO. They find that the candidates who appear more competent are more likely to become CEOs and get a larger pay, but they do not deliver superior performance. We next turn to the study of the largely unexplored role of first impressions based on visual cues in the context of early stage investors' investment decision-making, a setting characterized by a great deal of information asymmetry (Hochberg, Serrano, and Ziedonis, 2018; Howell 2020).

5.2 Measuring first impressions

We recruited survey respondents from the continental U.S. through Amazon Mechanical Turk (MTurk), 797 for the Shark Tank sample and 640 for the Startup Battlefield sample. The respondents took a Qualtrics survey designed to capture their first impressions of the entrepreneurs' facial traits. Figure 1 depicts the distribution of the physical locations of the survey respondents, indicating a wide geographic coverage.

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[12] See, for example, Hamermesh and Biddle (1994), Duarte, Siegel, and Young (2012), Kaplan, Klebanov, and Sorensen (2012), Graham, Harvey, and Puri (2017), Blankespoor, Hendricks, and Miller (2017), Cao et al. (2020), and Kaplan and Sorensen (2021).

< Figure 1 about here >

For each pitch, we take a standardized video still of the entrepreneurs. We resize the photographs so that the entrepreneurs' head sizes are similar. We randomly assign 20 photographs to each of the survey respondents and ask them to rate on a 9-point Likert scale their first impressions of the entrepreneurs' six facial traits. To foster comparability across respondents' ratings, we standardize their raw scores by calculating Z-scores. Let $R_{cd,i}$ denote respondent *i*'s rating regarding facial trait *d* of entrepreneur *c*. We compute the mean, $\mu_{d,i}$, and the standard deviation, $\sigma_{d,i}$, of the ratings on facial trait *d* across all the entrepreneurs rated by respondent *i* and then calculate the Z-score:

$$Z_{cd,i} = \frac{R_{cd,i} - \mu_{d,i}}{\sigma_d}. \tag{1}$$

The Z-score standardization ensures that the scores provided by all respondents share the same scale, with a zero mean and a unit standard deviation. The final score for entrepreneur *c* along facial trait *d* is the average of the Z-scores across all the N_c survey respondents who rated entrepreneur *c*:

$$Z_{cd} = \sum_{i=1}^{N_c} \frac{Z_{cd,i}}{N_c}. \tag{2}$$

5.3 Principal component analyses

First impressions of the entrepreneurs' six facial traits likely capture similar underlying factors, as evinced by their high correlations (Internet Appendix Table A4). Correlations among the scores capturing competence, confidence, trustworthiness, and the ability to handle pressure are high, ranging from 0.722 to 0.903, whereas correlations between the scores capturing these four and the remaining two facial traits (attractiveness and likability) are lower, ranging from 0.297 to 0.645. To streamline our analyses, we apply principal component analyses to the six facial traits for the Shark Tank and Startup Battlefield samples. In each sample, we retain the first two principal components for our subsequent regression analyses. These two components have eigenvalues larger than one and they jointly explain more than 85% of the variability in each sample; the remaining factors explain small incremental fractions of the variability and are likely unimportant.

Table 3 and Figure 2 feature the results of the principal component analyses for the Shark Tank sample (Panel A) and the Startup Battlefield sample (Panel B). For both samples, the component loadings affirm that the two components generated from the principal component analyses capture different aspects of the underlying characteristics. The first component has positive loadings on all six characteristics and can be naturally interpreted as general ability. By contrast, the second component has large, positive loadings on attractiveness and likability. These characteristics reflect the entrepreneurs' charm. The second component also has large negative loadings on competence, confidence, and ability to handle pressure. These characteristics reflect the entrepreneurs' managerial ability. Therefore, the second component distinguishes charming entrepreneurs from entrepreneurs with pronounced managerial ability. The former (charm) features positive values of the second component, whereas the latter (managerial ability) features negative values of the second component.[13] The component loadings plotted in Panels A and B of Figure 2 visualize for both samples the clustering of the facial traits that constitute each component.

The methodology we employ to extract the principal components that capture first impressions is remarkably robust across the Shark Tank show and the Startup Battlefield competitions. Panel C of Figure 2 compares the loadings of the two components on the six facial traits across the two samples. This comparison shows that distinct samples of survey respondents who rated entrepreneurs from distinct settings yielded virtually identical component loadings for the two principal components. These findings not only suggest a robust way of capturing first impressions of facial traits but also open a pathway toward an automated approach that could rely on facial recognition technology and machine learning. Such data collection methodology has begun to emerge in the finance and economics literature (Gomulya et al., 2017; Halford and Hsu, 2020; Hu and Ma, 2021; Peng et al., 2022).

< Table 3 about here >

< Figure 2 about here >

6. Angel Investors' Decision-Making, Post-Event Business Outcomes, and First Impressions

As a first look, we observe univariate relations between angel investors' decisions and the first impressions entrepreneurs convey through facial traits. We summarize these analyses in the Internet Appendix by presenting binned scatterplots that display the probability of angel investors

[13] These two principal components are highly consistent with the factor analysis of CEO candidate characteristics in Kaplan, Klebanov, and Sorensen (2012), as well as of the factor analysis of CEO, CFO, COO, and CXO candidate characteristics in Kaplan and Sorensen (2021). Their first factor is also naturally interpreted as general ability, and their second factor distinguishes between candidates with greater interpersonal skills and candidates with greater execution ability.

making an investment offer or Startup Battlefield judges selecting a competition round winner against the decile of each of the six facial traits (Figure A1). The graphs reveal largely positive and statistically significant (albeit somewhat noisy) univariate correlations. The graphs also suggest that the correlations we study are not driven by the tails of the facial traits score distributions. We proceed with multivariate analyses by relying on the two principal components extracted from first impressions of the six facial traits.

Section 6.1 focuses on the role first impressions of entrepreneurs' facial traits play in angel investors' decisions to select a business. Section 6.2 focuses on the relation between post-show or post-competition business outcomes and the first impressions entrepreneurs convey through facial traits. Finally, Section 6.3 uses the results from Sections 6.1 and 6.2 to deliver a nuanced picture of the relation between angel investors' decisions and first impressions, particularly whether their decisions reflect rational or behavioral tendencies.

6.1 Angel investors' decision-making and first impressions

Our first analysis uses the pooled sample of Shark Tank and Startup Battlefield pitches to estimate the probability of winning—receiving an investment offer (Shark Tank) or winning a competition round (Startup Battlefield). The dependent variable Win_{ct} indicates whether entrepreneur (team) c in season/competition t receives an investment offer/wins the competition round. We employ a logit model,

$$P(Win_{ct} = 1 \mid gen_{ct}, cvm_{ct}, X_{ct}, \eta_t, \iota_c) = \Lambda(\beta_0 + \beta_1 gen_{ct} + \beta_2 cvm_{ct} + T' X_{ct} + \eta_t + \iota_c), \quad (3)$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function, and gen_{ct} (general ability) and cvm_{ct} (charm versus managerial ability) are the two principal components of the normalized facial trait scores the survey respondents assigned to the entrepreneur (team) c in season/competition t. We also estimate and report an equivalent OLS linear probability model.

We control for X_{ct}, the information we obtained for the business pitched by entrepreneur (team) c in season/competition t. Specifically, we include the indicator variables *Team* (set to 1 if the business has been pitched by a team and set to 0 otherwise), *Female* (set to 1 if the business has been pitched by a solo female entrepreneur or an all-female team and set to 0 otherwise), and *Calculation Error* (a proxy for entrepreneurs' performance during the pitch, set to 1 if the entrepreneur (team) committed a noticeable calculation error during the pitch and set to 0 otherwise). We use indicator variables to capture the team members' highest level of educational attainment and professional experience, patent status, and the stage of the entrepreneurs' businesses. We also control for the entrepreneurs' asking business valuations, annualized past sales, and self-investment amounts (Shark Tank) and funds raised before the competition (Startup Battlefield).[14] Finally, we include season/competition fixed effects η_t, and industry fixed effects ι_c.

Table 4 presents the results of estimating the specification from Eq. (3). Columns (1) and (2) feature estimates of the logit specifications, and columns (3) and (4) feature estimates of the corresponding OLS specifications. Coefficients associated with the entrepreneurs' general ability (*gen*) and the entrepreneurs' charm versus managerial ability (*cvm*) are positive and statistically significant in both the specifications without any controls (columns (1) and (3)) and with the full set of controls (columns (2) and (4)).

[14] The list of available covariates in the Shark Tank and Startup Battlefields is very similar, but not identical. Whereas entrepreneurs' asking business valuations, annualized past sales, and self-investment amounts are available only for the Shark Tank pitches, fund raised before the competition are available only for the Startup Battlefield pitches. To address this issue, we perform imputation by using the stata `mi impute chained` command (Raghunathan et al., 2001). It fills in missing values in multiple variables iteratively by using chained equations, a sequence of univariate imputation methods with fully conditional specification (FCS) of prediction equations. It accommodates arbitrary missing-value patterns. To account for the uncertainty of the imputed value, we chose 20 imputations.

To assess economic magnitudes of first impression variables, we focus on the logit estimates from the full specification (column (2) of Table 4). Panel C of Table 1 and Panel C of Table 2 suggest that the baseline unconditional probability of a win is 43.09%.[15] An increase in the entrepreneurs' general ability from the 25th percentile to the 75th percentile of its distribution is associated with a 5.45 percentage point increase in the implied probability of winning, a 12.65 percent increase (5.45 pp/43.09%) relative to the baseline unconditional probability. Similarly, an interquartile increase in the entrepreneurs' charm versus managerial ability is associated with a 10.06 percentage point increase in the implied probability of winning, a 23.35 percent increase (10.06 pp/43.09%) relative to the baseline unconditional probability.

The negative coefficients associated with *Calculation Error* suggest that the probability of winning declines if the entrepreneur commits a noticeable calculation error during the pitch. For example, based on the point estimate from the linear specification (column (4)) of –0.136, committing a noticeable calculation error is associated with a 14.9 percentage point decline in the implied probability of winning, a 31.56 percent decline (–13.6 pp/43.09%) relative to the baseline unconditional probability. This finding suggests another important contribution of our work—we show that the substantive information revealed *during* real-time interactions (taking place after the first impressions have been imparted) also affects the angel investors' or judges' decision-making.[16]

Table 4 also shows that the probability of an entrepreneur (team) winning is associated with neither *Team* nor *Female* indicator variables. The entrepreneurs' educational background and

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[15] Out of 379+352 = 731 pitches in our sample, 229 have received an offer on Shark Tank, and 86 have won a Startup Battlefield competition round, implying the unconditional winning probability of (229+86)/731 = 0.4309.

[16] Hu and Ma (2021) focus on persuasive communication during a pre-recorded video pitch by capturing its positivity, passion, and warmth. Whereas persuasiveness of communication as measured by Hu and Ma (2021) does not consider the quality of the pitch performance (captured in our context by *Calculation Error*), it too suggests that there are cues imparted during the pitch that have the potential to affect outcomes.

professional experience also do not appear to matter. The lack of findings concerning entrepreneur gender and education is consistent with Boulton et al. (2019), who document non-significant results on entrepreneurs' gender, race, and education in a sample of Shark Tank pitches. Finally, businesses with patents appear more likely to receive offers.

< Table 4 about here >

6.2 Post-event business outcomes and first impressions

Our analyses of winning in the Shark Tank and Startup Battlefield contexts provide consistent evidence that there is a positive relation between the probability of a favorable outcome (receiving an offer from investors or being selected as a competition round winner) and both entrepreneurs' general ability and charm versus managerial ability. These findings suggest that angel investors' decision-making is related to first impressions that entrepreneurs convey through facial traits. In this section, we focus on the post-event outcomes of the entrepreneurs' businesses by testing whether first impressions of entrepreneurs' general ability and charm versus managerial ability help predict how their businesses will perform after they appear on Shark Tank or in a Startup Battlefield competition.

The post-event business outcome is captured as an ordinal variable with three categories: *Home Run*, *Operating*, and *Failure* (see Section 4 for details). We relate the post-event outcomes to first impressions of entrepreneurs' general ability and charm versus managerial ability, while controlling for other variables and fixed effects employed in previous analyses (Section 6.1). Table 5 reports estimation results for an ordered logit model (column (1)) and a linear probability model (column (2)). The estimates associated with first impressions of the entrepreneurs' general ability (*gen*) are positive and statistically significant. On the other hand, the estimates associated with first impressions of the entrepreneurs' charm versus managerial ability (*cvm*) are *negative* and statistically significant. These results indicate that first impressions of entrepreneurs' general ability and charm versus managerial ability help predict the business outcome and, therefore, contain information relevant for angel investors' investment selection.

< Table 5 about here >

6.3 Relation between angel investor decisions and first impressions: Rational or behavioral?

In this section, we evaluate the rationality of angel investors' decisions. On the one hand, consistent with a neoclassical explanation, first impressions could be an observable indicator that predicts performance. They might capture startup quality, and pursuing investment decisions in line with the first impressions based on facial traits might be rational. On the other hand, consistent with a behavioral explanation, first impressions might not convey performance-related information, or even might convey misleading performance-related information. As a result, pursuing investment decisions in line with first impressions might be irrational.

Empirical evidence from the previous sections suggests that angel investors internalize first impressions of general ability in a manner consistent with rationality. Both the relation between angel investors'/competition judges' propensity to select a winning startup and first impressions of entrepreneurs' general ability (Section 6.1) and the relation between subsequent business outcome and first impressions of entrepreneurs' general ability (Section 6.2) are positive. The pattern is the opposite for charm versus managerial ability. The relation between angel investors'/competition judges' propensity to select a winning startup and first impressions of entrepreneurs' charm versus executive ability is positive (Section 6.1), indicating that angel investors/competition judges favor charm over managerial ability when selecting the winning pitches. On the other hand, the relation between subsequent business outcome and first impressions of entrepreneurs' charm versus managerial ability is *negative* (Section 6.2), suggesting that what matters for success is the entrepreneurs' managerial ability, rather than charm. Therefore, angel investors in our sample subscribe to a variant of the beauty premium (Hamermesh and Biddle, 1994).

An integral component of charm in our decomposition is attractiveness. The role of attractiveness in the labor market is far from conclusive. Early research has documented a beauty premium in the labor market (Hamermesh and Biddle, 1994; Biddle and Hamermesh, 1998; Harper, 2000; Robins, Homer, and French, 2011; Scholz and Sicinski, 2015). On the other hand, some studies show that attractive female job applicants face a beauty penalty (Agthe et al., 2010). Recently, Stinbrickner, Stinbrickner, and Sullivan (2019) argue that the beauty premium only exists in connection with the jobs that require a lot of interpersonal interaction, but not in those that demand skills for working with information and data. Their findings indicate that the beauty premium is not driven by employer-based discrimination, but by the nature of the jobs. In addition, they find that more attractive workers tend to sort into jobs that value beauty.

The role of attractiveness also varies across cultures (e.g., Li et al., 2020; Ruffle and Shtudiner, 2015),[17] professions (e.g., Graham, Harvey, and Puri, 2017; Peng et al., 2022),[18] contexts, and job types. Our analyses in the context of entrepreneurial investment bring evidence of a beauty premium. Indeed, angel investors from our sample reward charm despite its negative association with subsequent success or, equivalently, disregard managerial ability despite its positive

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[17] Li et al. (2020) report a stark contrast across different cultures: beauty does not affect the likelihood of being voted as an all-star analyst in the U.S., but it does so in China. Ruffle and Shtudiner (2015) find that in the Israeli labor market more attractive female job applicants tend to receive a lower callback rate than other female applicants do.

[18] Peng et al. (2022) study the relation between U.S. analysts' forecast accuracy and their facial traits (trustworthiness, dominance, and attractiveness). They find that forecast accuracy is not associated with attractiveness and is positively associated with trustworthiness and dominance. Graham, Harvey, and Puri (2017) examine the relation between CEO selection and compensation and beauty. They find no premium associated with beauty but a premium for the look of competence (competent looks are associated with higher pay, but not with superior future performance).

association with subsequent success. This tendency does not reflect economically-motivated rational behavior; rather, it appears primarily rooted in a behavioral explanation.

This pattern highlights a nuanced interpretation of first impressions of facial traits. Usually, a study advances either rational explanations (e.g., Halford and Hsu, 2020) or behavioral ones (e.g., Graham, Harvey, and Puri, 2017). Our study presents novel evidence that angel investors rationally internalize first impressions of general ability and irrationally internalize first impressions of charm versus managerial ability.

7. The Role of Experience

Classical learning-by-doing models (Arrow, 1962; Grossman, Kihlstrom, and Mirman, 1977) suggest that angel investors might improve their investment selection skill as they learn from past experiences. Whereas evidence of early stage investors' learning from their experiences is scarce, improvement in decision-making with experience has been documented for other economic agents, including entrepreneurs (Howell, 2021), mutual-fund managers (Kempf, Manconi, and Spalt, 2017), IPO auction participants (Chiang et al., 2011), individual investors (Feng and Seasholes, 2005; Seru, Shumway, and Stoffman, 2010), and security analysts (Mikhail, Walther, and Williams, 1997). To shed light on the role of experience in improving angel investors' decision-making, we turn to the Shark Tank setting, in which we can observe the investors' individual decisions for each pitch. The Shark Tank setting allows us to test whether angel investors learn from their experiences over time and mitigate the biases in their decision-making associated with the first impressions conveyed through facial traits.

7.1 Measuring investors' experience

A total of ten angel investors appear on the five seasons of Shark Tank. They have been introduced to the show at different points in time. In addition, at the beginning of the first season of Shark Tank, Robert Herjavec and Kevin O'Leary have had three years of similar experience through their participation in Dragons' Den (the Canadian version of the Shark Tank show, predating Shark Tank by three seasons). The other investors joined Shark Tank without prior experience. The staggered introduction of the core team of six investors over the years, departures of some investors, and the occasional presence of guest investors create sufficient variation in the investors' level of experience with decision-making on the show.

To measure experience, for each investor-pitch observation, we calculate the variable Experience as the natural logarithm of one plus the number of past pitches in which the investor had participated (in Shark Tank or Dragons' Den) prior to the current pitch. Panel A of Table 6 reports the distribution of investors' experience across the 1,895 investor-pitch observations.

7.2 Regression analysis

To investigate the effect of experience on investors' decision-making, we conduct regression analyses of the probability that an investor would make an investment offer (similar to Eq. (3)), with the measure of experience and additional interaction terms between the first impression components and the experience measure. The specifications include the same control variables and fixed effects as reported in Table 4. We also add investor fixed effects. Their presence helps address the concern that any variation we observe might be driven by differences across individual investors rather than differences in their experience. Panel B of Table 6 presents the estimation results of both the logit and linear probability models.

The first two rows in Panel B display regression coefficients associated with general ability and charm versus managerial ability. They capture the role that first impressions play in the inexperienced investors' investment decision-making. The third row features Experience, and the next two rows present the coefficients associated with the interactions between first impressions of general ability (*gen*) and charm versus managerial ability (*cvm*) and Experience. The bottom three rows of Panel B report post-estimation tests for the sums of the coefficients associated with the first impressions and the interaction terms, capturing the role that first impressions play across various levels of investors' investment decision-making experience.

The main takeaway from Table 6 is associated with charm versus managerial ability (*cvm*). The second row in Panel B documents a positive and statistically significant association between the probability that a less experienced investor will extend an offer and first impressions of the entrepreneur's charm versus managerial ability (*cvm*). The key result is the negative and statistically significant coefficient associated with the interaction term between charm versus ability (*cvm*) and an investor's experience (fifth row in Panel B), suggesting that this relation grows weaker with an investor's experience. Indeed, as shown in the last three rows of Panel B, the relation weakens as the investor experience moves across quartiles of its distribution. Ultimately, it is not statistically significant for the observations at the 75^{th} percentile of the investor experience distribution. Overall, these results are consistent with the notion that experience—learning-by-doing—mitigates irrational tendencies in investors' decision-making along the dimension of first impressions of entrepreneurs' charm versus managerial ability (*cvm*).

< Table 6 about here >

8. Conclusion

This paper examines the role of first impressions in early stage investors' decision-making. We focus on first impressions regarding six facial traits (competence, confidence, trustworthiness, the ability to handle pressure, physical attractiveness, and likability). Relying on early stage entrepreneurial business pitches on a reality TV show (Shark Tank) and a technology startup competition (Startup Battlefield), we capture video stills of entrepreneurs' faces and ask samples of U.S. survey respondents to rate the entrepreneurs' facial traits. To reduce the dimensionality of the facial traits, we apply principal component analyses to extract two principal components: general ability (*gen*) and charm versus managerial ability (*cvm*).

We uncover positive and statistically significant associations between the likelihood of entrepreneurs receiving an investment offer or winning a competition round and first impressions of entrepreneurs' general ability and charm versus managerial ability. We also find that post-event business success is positively associated with first impressions of entrepreneurs' general ability. At the same time, future business success is negatively associated with first impressions of entrepreneurs' charm versus managerial ability, highlighting the importance of managerial ability for success. These findings suggest that angel investors appear to internalize first impressions of entrepreneurs' general ability rationally, but exhibit behavioral, irrational tendencies in the way they internalize first impressions of entrepreneurs' charm versus managerial ability. The extant literature features studies that advance either rational explanations (e.g., Halford and Hsu, 2020) or behavioral, irrational explanations (e.g., Graham, Harvey, and Puri, 2017). Our study provides prima facie evidence that economic agents, in this instance angel investors, rationally internalize some visual cues and, at the same time, irrationally utilize others.

Finally, we explore whether angel investors learn as they obtain experience in investment decision-making. Our evidence that gaining experience reduces angel investors' tendency to internalize irrationally first impressions of entrepreneurs' charm versus managerial ability provides evidence that supports the classical learning-by-doing models (Arrow, 1962; Grossman, Kihlstrom, and Mirman, 1977). Given the high levels of information asymmetry in early stage investment decisions (Hochberg, Serrano, and Ziedonis, 2018; Howell 2020), mitigating irrational use of human visual cues could help angel investors improve their investment decision-making.

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Table 1
Shark Tank sample summary statistics.

This table contains summary statistics for the 379 pitches from the first five Shark Tank seasons. Panel A reports summary statistics for the entrepreneur characteristics. Panel B reports summary statistics for the pitched business characteristics. Panel C reports summary statistics for the variables related to shark investors' decisions. Panel D reports the distribution of post-show outcomes.

	N	Mean	S.D.	Min	P25	Median	P75	Max
Panel A: Entrepreneur characteristics								
Calculation Error	379	0.16						
Presentation format								
Team	379	0.41						
Female (solo female or all-female team)	379	0.26						
Education (omitted category: Below college)								
Graduate/professional	379	0.17						
Bachelor's degree	379	0.37						
Experience (omitted category: Other)								
Executive	379	0.30						
Professional	379	0.18						
Panel B: Business characteristics								
Asking terms								
Cash amount ($ in thousands)	379	246	428	10	75	150	250	5,000
Equity share (%)	379	18.63	10.38	3.00	10.00	20.00	25.00	100.00
Asking business valuation ($ in thousands) (*ask* = Cash amount/Equity share)	379	1,881	3,395	40	400	850	2,000	30,000
Patent status (omitted category: N/A)								
Approved	379	0.21						
Pending	379	0.10						
Rejected	379	0.03						
Business stage (omitted category: N/A)								
Early	379	0.26						
Growth	379	0.13						
Expansion	379	0.10						
Past sales ($ in thousands)	379	357	740	0	10	80	315	5,100
Self-investment ($ in thousands)	379	78	303	0	0	0	20	4,000
Panel C: Shark investors' decisions								
Pitch level								
# offers made to the business								
0	379	0.40						
1	379	0.22						
2-4	379	0.30						
5-10	379	0.08						
Shark investor-pitch level								
Shark investor made an offer (%)	1,895	25.96						
Panel D: Post-show outcomes								
Home Run	379	0.07						
Operating	379	0.68						
Failure	379	0.25						

Table 2
Startup Battlefield sample summary statistics.

This table contains summary statistics for the 352 pitches from 19 Startup Battlefield competitions hosted in New York, San Francisco, Berlin, and London between 2013 and 2019. Panel A reports summary statistics for the entrepreneur characteristics. Panel B reports summary statistics for the pitched business characteristics. Panel C reports summary statistics for the variables related to the competition judges' decisions. Panel D reports the distribution of post-competition outcomes.

Panel A: Entrepreneur characteristics								
	N	Mean	S.D.	Min	P25	Median	P75	Max
Calculation Error	352	0.02						
Presentation format								
Team	352	0.78						
Female (main presenter)	352	0.19						
Education (omitted category: Below college)								
Graduate/professional	352	0.54						
Bachelor's degree	352	0.38						
Experience (omitted category: Other)								
Executive	352	0.14						
Professional	352	0.47						
Panel B: Business characteristics								
	N	Mean	S.D.	Min	P25	Median	P75	Max
Patent status (omitted category: # Patents = 0)								
# Patents ≥ 3	352	0.11						
# Patents 1 or 2	352	0.11						
# Patents	352	1.66	8.36	0.00	0.00	0.00	0.00	137.00
Business stage (omitted category: Early (firm age < 3 yrs))								
Growth (firm age ≥ 3 yrs)	352	0.16						
Firm age (in years)	352	1.39	1.49	0.00	1.00	1.00	2.00	13.00
Funds raised pre-competition ($ in thousands)	352	544	1,522	0	0	0	250	15,200
Panel C: Competition judges' decisions								
	N	Mean	S.D.	Min	P25	Median	P75	Max
Won Competition Round (%)	352	24.43						
Competition finals (%)								
Winner	352	4.83						
Runner-up	352	4.83						
Finalist	352	14.77						
Panel D: Post-competition outcomes								
	N	Mean	S.D.	Min	P25	Median	P75	Max
Home Run	352	0.03						
Operating	352	0.85						
Failure	352	0.12						

Table 3
First impressions of entrepreneurs' facial traits: Principal component analyses.

This table contains the key results of the principal component analyses of first impressions of entrepreneurs' facial traits for the Shark Tank (Panel A) and Startup Battlefield (Panel B) samples. Measurement of first impressions of entrepreneurs' facial traits is described in Section 5.2. Principal component analyses for the Shark Tank and Startup Battlefield samples are described in Section 5.3.

Panel A: Shark Tank sample

Summary statistics of component scores:	Mean	S.D.	Min	P25	Median	P75	Max
Component 1: General ability (*gen*)	0.00	2.02	−6.40	−1.36	0.21	1.39	5.54
Component 2: Charm vs. managerial (*cvm*)	0.00	1.03	−3.21	−0.69	−0.05	0.69	3.10

Principal component loadings:	Component 1: General ability (*gen*)	Component 2: Charm vs. managerial (*cvm*)
Competence	0.4508	−0.3090
Confidence	0.4426	−0.1008
Trustworthiness	0.4606	−0.0453
Ability to handle pressure	0.4373	−0.4002
Attractiveness	0.3042	0.6184
Likability	0.3240	0.5915
Proportion of variance explained (%):	68.00	17.54

Panel B: Startup Battlefield sample

Summary statistics of component scores:	Mean	S.D.	Min	P25	Median	P75	Max
Component 1: General ability (*gen*)	0.00	2.09	−6.49	−1.35	0.21	1.56	5.04
Component 2: Charm vs. managerial (*cvm*)	0.00	0.92	−3.08	−0.54	−0.02	0.52	2.42

Principal component loadings:	Component 1: General ability (*gen*)	Component 2: Charm vs. managerial (*cvm*)
Competence	0.4355	−0.3144
Confidence	0.4192	−0.2390
Trustworthiness	0.4289	0.0101
Ability to handle pressure	0.4225	−0.4425
Attractiveness	0.3586	0.5770
Likability	0.3789	0.5614
Proportion of variance explained (%):	72.73	14.07

Table 4

Probability of receiving an investment offer or winning a competition round.

This table uses the combined sample of Shark Tank (ST) and Startup Battlefield (SB) pitches to report the results of logit and linear probability regressions that estimate the probability of a win (receiving an investment offer on a Shark Tank show or winning a Startup Battlefield competition round), as described in Section 6.1, Eq. (3). The dependent variable is an indicator variable set to 1 if the contestant wins and set to 0 otherwise. The key independent variables are the two principal components capturing entrepreneurs' general ability (*gen*) and charm versus managerial ability (*cvm*). Controls are indicator variables *Calculation Error* (an indication of whether the presenter made a calculation error during the pitch), *Team* (capturing the team presentation format), and *Female* (capturing solo female entrepreneurs or teams consisting of only female entrepreneurs), variables capturing the entrepreneurs' highest educational attainment and experience, the natural logarithm of entrepreneurs' asking business valuation, the natural logarithm of annualized past sales, the natural logarithm of the self-investment amount, the natural logarithm of the funds raised pre-competition, and the indicator variable *Patent* (capturing whether a Shark Tank business has an approved patent or whether a Startup Battlefield business has at least three patents). The regressions also feature business stage fixed effects, Shark Tank season/Startup Battlefield competition fixed effects and industry fixed effects. Robust standard errors are reported in parentheses alongside the corresponding regression coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: *Win* (=1: Receive an offer from shark investors or win a Startup Battlefield competition round; =0: Otherwise)	Logit				Linear probability			
	(1)		(2)		(3)		(4)	
	Coef. estimate	Std. error	Coef. estimate	Std. error	Coef. estimate	Std. error	Coef. estimate	Std. error
General ability (*gen*)	0.078**	(0.037)	0.080*	(0.045)	0.019**	(0.009)	0.015*	(0.009)
Charm versus managerial (*cvm*)	0.194**	(0.077)	0.331***	(0.113)	0.047**	(0.019)	0.063***	(0.021)
Calculation Error			–0.652**	(0.330)			–0.136**	(0.068)
Team			0.001	(0.217)			0.001	(0.042)
Female			–0.153	(0.254)			–0.027	(0.049)
Education (omitted: Below college)								
Bachelor's degree			0.245	(0.258)			0.049	(0.052)
Graduate/professional			0.096	(0.276)			0.022	(0.054)
Experience (omitted: Other)								
Professional			0.207	(0.236)			0.037	(0.045)
Executive			0.193	(0.255)			0.040	(0.050)
ln(entrepreneurs' *ask* valuation)			0.012	(0.150)			0.003	(0.028)
ln(past sales)			0.082	(0.075)			0.014	(0.014)
ln(self-investment)			0.103	(0.065)			0.019	(0.012)
ln(funds raised pre-competition)			0.034	(0.063)			0.006	(0.012)
Patent			1.040***	(0.271)			0.201***	(0.053)
Fixed effects:								
Business stage	No		Yes		No		Yes	
ST season/SB competition	No		Yes		No		Yes	
Industry	No		Yes		No		Yes	
N	731		731		731		731	
(Pseudo) R^2	0.011		0.196		0.015		0.242	
Baseline (unconditional) probability of winning:								
	43.09%		43.09%		43.09%		43.09%	
Change in probability of winning for interquartile change (25th to 75th percentile) in:								
General ability (*gen*)	5.36%		5.45%		5.28%		4.26%	
Charm versus managerial (*cvm*)	5.98%		10.06%		5.93%		7.90%	

Table 5
Post-show outcomes.

This table reports the results of ordered logit and linear regressions that relate the outcomes for businesses appearing on the Shark Tank show or in a Startup Battlefield competition with the key independent variables capturing the first impressions of entrepreneurs' general ability (*gen*) and charm versus managerial ability (*cvm*). The dependent variable, Outcome, is an ordinal variable with categories *Home Run*, *Operating*, and *Failure*, as described in Section 4. Controls are indicator variables *Calculation Error* (an indication of entrepreneurs committing a calculation error during the pitch), *Team* (capturing the team presentation format), *Female* (capturing solo female entrepreneurs or teams consisting of only female entrepreneurs), and *Win* (the indicator of receiving an investment offer on a Shark Tank show or winning a Startup Battlefield competition round), variables capturing the entrepreneurs' highest educational attainment and experience, the patent status, the natural logarithm of annualized past sales, the natural logarithm of the entrepreneurs' self-investment amount, and the natural logarithm of the funds raised pre-competition. The regressions also include the business stage fixed effects, Shark Tank season/Startup Battlefield fixed effects, and industry fixed effects. Robust standard errors are reported in parentheses alongside the corresponding regression coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Outcome (= 1: *Home Run*, = 0: *Operating*, = –1: *Failure*)	Ordered logit (1)		Linear model (2)	
	Coef. estimate	Std. error	Coef. estimate	Std. error
General ability (*gen*)	0.137**	(0.058)	0.020**	(0.009)
Charm versus managerial (*cvm*)	–0.239*	(0.133)	–0.037*	(0.021)
Calculation Error	0.024	(0.485)	–0.006	(0.081)
Team	0.334	(0.315)	0.054	(0.049)
Female	–0.010	(0.297)	–0.001	(0.048)
Win	1.041***	(0.247)	0.162***	(0.040)
ln(entrepreneurs' *ask* valuation)	0.124	(0.295)	0.018	(0.046)
ln(past sales)	0.292*	(0.156)	0.045**	(0.022)
ln(self-investment)	–0.122	(0.114)	–0.019	(0.018)
ln(funds raised pre-competition)	0.257**	(0.123)	0.039**	(0.017)
Other controls:				
Education	Yes		Yes	
Experience	Yes		Yes	
Patent	Yes		Yes	
Fixed effects:				
Business stage	Yes		Yes	
ST season/SB competition	Yes		Yes	
Industry	Yes		Yes	
N	731		731	
(Pseudo) R^2	0.230		0.269	

Table 6
The role of shark investors' experience.

Panel A reports the distribution of the shark investors' experience level across the 1,895 shark investor-pitch observations. For each shark investor-pitch observation, the variable Experience is calculated as the natural logarithm of one plus the number of past pitches in which the shark investor had participated (in Shark Tank of Dragons' Den) prior to the current pitch. Panel B reports the results of both logit and linear probability regressions that estimate the probability of a shark investor makingan investment offer to an entrepreneur (or team). The specification is similar to Eq. (3), as described in Section 6.1, with the addition of the respective variable that measures shark investor experience and its interactions with general ability (*gen*) and charm versus managerial ability (*cvm*), as well as shark investor fixed effects. The bottom three rows of the table present charm versus managerial ability (*cvm*) post-estimation tests by experience percentiles PExperience for lower level of experience (P25), intermediate level of experience (Median), and high level of experience (P75). Robust standard errors in Panel B are reported in parentheses alongsidethe corresponding regression coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Distribution of shark investor experience								
	N	Mean	S.D.	Min	P25	Median	P75	Max
#Past Pitches	1,895	245	196	0	94	186	346	725
Experience (= *ln*(1+#Past Pitches))	1,895	5.048	1.162	0	4.554	5.231	5.849	6.588

Panel B: Regression results				
Dependent variable:	Logit		Linear probability	
Shark investor offer	(1)		(2)	
(= 1 if shark investor makes an investment offer, = 0 otherwise)	Coef. estimate	Std. error	Coef. estimate	Std. error
General ability (*gen*)	0.039	(0.129)	0.002	(0.023)
Charm versus managerial (*cvm*)	0.616**	(0.254)	0.111**	(0.044)
Experience	–0.017	(0.060)	–0.004	(0.011)
General ability (*gen*) x Experience	0.004	(0.025)	0.002	(0.004)
Charm versus managerial (*cvm*) x Experience	–0.085*	(0.048)	–0.015*	(0.008)
Calculation Error	–0.506***	(0.170)	–0.081***	(0.025)
Controls for entrepreneur and business characteristics	Yes		Yes	
Fixed effects:				
Shark investor	Yes		Yes	
Season	Yes		Yes	
Industry	Yes		Yes	
N	1,895		1,895	
(Pseudo) R^2	0.061		0.067	
Charm versus managerial (*cvm*) post-estimation tests by experience percentiles (*cvm* + *cvm* x PExperience):				
PExperience = P25 = 4.554	0.231***	(0.074)	0.041***	(0.013)
PExperience = Median = 5.231	0.173**	(0.070)	0.030**	(0.012)
PExperience = P75 = 5.849	0.121	(0.079)	0.021	(0.014)

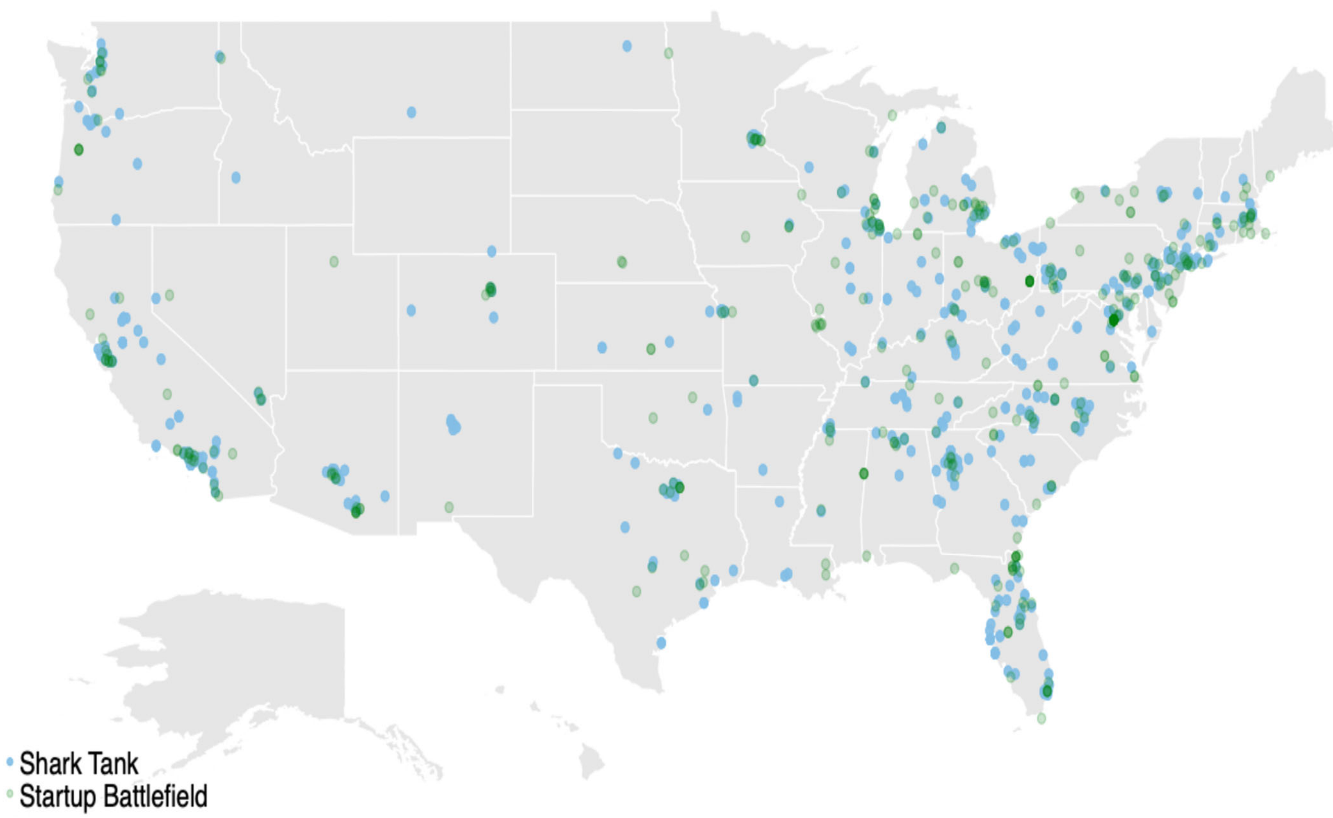
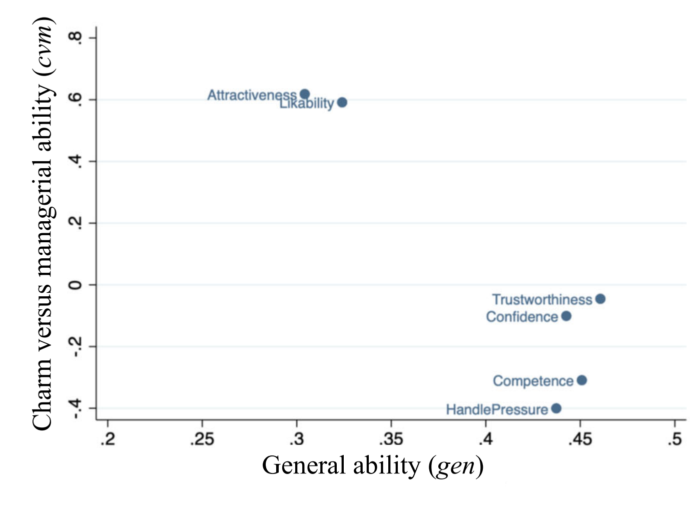
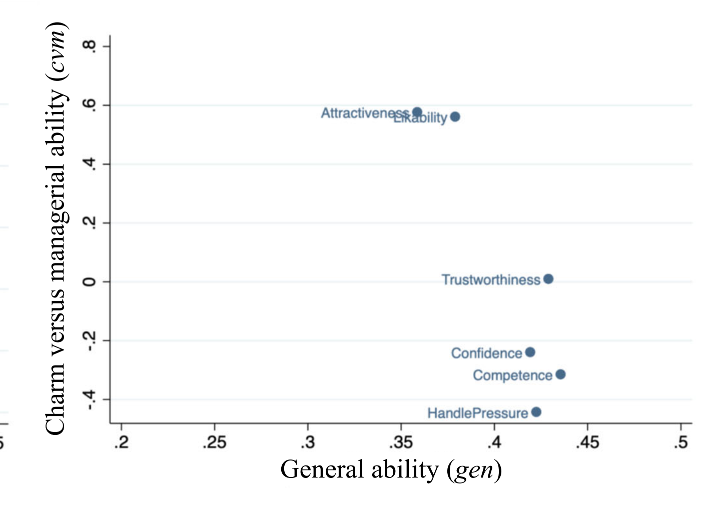


Fig. 1: This figure depicts the locations of the 797 survey respondents who rated Shark Tank entrepreneurs' facial traits (blue dots) and the locations of the 640 survey respondents who rated Startup Battlefield entrepreneurs' facial traits (green dots). The survey was fielded to respondents located in the continental U.S.A. Their locations on the map are based on their IP addresses.

Panel A: Shark Tank sample component loadings



Panel B: Startup Battlefield sample component loadings



Panel C: Comparison of principal component loadings (Shark Tank vs. Startup Battlefield)

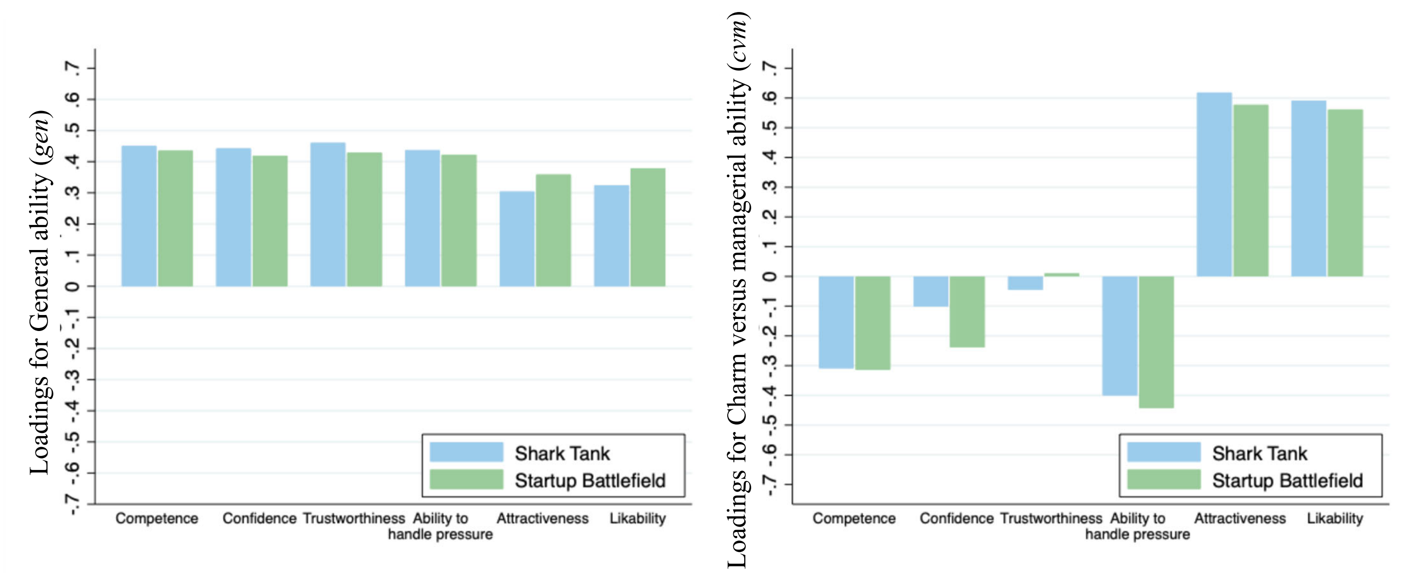


Fig. 2. This figure illustrates the principal component analyses presented in Table 3. Panels A and B plot the component loadings for the principal component analyses of the Shark Tank (Panel A) and Startup Battlefield (Panel B) samples of survey respondents' ratings of entrepreneurs' facial traits. Panel C compares principal component loadings for general ability (*gen*, left) and charm versus managerial ability (*cvm*, right) between the Shark Tank and Startup Battlefield samples.

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Internet Appendix

Table A1 Industry classification and business examples.

This table reports the industry classification and business examples for the Shark Tank (Panel A) and Startup Battlefield (Panel B) samples.

Panel A: Shark Tank sample		
Industry	Business example	Product description
Food	Element Bars	Customized energy bars; select own type of bar and labels
Clothes and accessories	HoodiePillow	Pillow with an attached hood; has a pouch for a phone or remote and a headphone slit
Home, garden, and furnishings	Fridge Fronts	Kitchen appliance decor: magnetic sheets with colorful images to cover the surfaces of refrigerators, ranges or dishwashers
Novelty items	Wake N Bacon	Alarm clock that wakes you up with bacon
Health and related	Nitroforce Titan 1000	A piece of workout equipment that can offer many different forms of workout
Baby and kid items	Ride-On Carry-On	Device that attaches to luggage that is a seat for young children so you do not have to bring a stroller to the airport
Services and events	Games2U	Mobile entertainment company that brings games to children's parties
Tech, gadgets, and apps	VerbalizeIt	A company that connects you to its community of translators and allows its translators to communicate on your behalf through an app or website
Sports and outdoors	Tower Paddle Boards	Paddle boards, surf boards that you use with a paddle
Education, info, and related	Classroom Jams	Teaching product in which Shakespeare and other lessons are put into songs; sold in DVD form

Panel B: Startup Battlefield sample		
Industry	Business example	Product description
Software	Discord	Online voice, video, and text service
Information technology	Trillium Secure	In-vehicle cybersecurity protection for connected vehicles
Hardware	Roadie Music by Band Industries	Musician's producing toolkit
Health and related	Future Family	Affordable fertility care
FinTech/Data service	N26	Mobile banking
Other	Lori Systems	Logistics infrastructure for trucking

Table A2 Industry distribution.

This table reports the industry distribution for the Shark Tank (Panel A) and Startup Battlefield (Panel B) samples.

Panel A: Shark Tank sample		
Industry	N	Mean
Food	379	0.17
Clothes and accessories	379	0.13
Home, garden, and furnishings	379	0.11
Novelty items	379	0.10
Health and related	379	0.08
Baby and kid items	379	0.08
Services and events	379	0.07
Tech, gadgets, and apps	379	0.05
Sports and outdoors	379	0.04
Education, info, and related	379	0.04
Other	379	0.10
Panel B: Startup Battlefield sample		
Industry	N	Mean
Software	352	0.63
Information technology	352	0.16
Hardware	352	0.06
Health and related	352	0.06
FinTech/Data service	352	0.05
Other	352	0.05

Table A3 Home run businesses.

This table lists home run businesses for the Shark Tank (Panel A) and Startup Battlefield (Panel B) samples.

Panel A: Shark Tank Home Runs

Business	Comment
Bouqs	Exceeded $100M in sales by 2019
Bubba's Q Boneless Ribs	$16M in sales in 2017; $25M in sales in 2019
Chef Big Shake Foods	$5-6M in annual sales
CordaRoy's	$48M in sales by 2019
Cousins Maine Lobster	$67M in sales by 2019
Cycloramic	Acquired in 2018 by Carvana for $22M
Doorbot (Ring)	$415M in sales by 2017; acquired by Amazon in 2018 for $1.1B
Drop Stop	$38M in sales by 2019
FiberFix	$66M in sales by 2019
Grace and Lace	$36M in sales by 2018
Groovebook	$26M in sales; sold to Shutterfly in 2014 for $14.5M
Kodiak Cakes	Reached over $160M in annual sales by 2018
Mission Belt	$25M in sales by 2019
Nuts 'N More	$30M in sales by 2018
Plated	$100M+ in sales by 2015; acquired by Albertsons for $200M plus additional benefits
Pork Barrel BBQ	$15M in sales by 2016; $4M from sauces annually
ReadeREST	$38M in sales by 2019
Rugged Races	$10.5M in sales in 2016; acquired by New Media Investment Group in 2018 for $10.4M
Scan	Acquired by Snapchat for $54M in cash and Snapchat stocks
Scrub Daddy	$209M in sales by 2019
Simple Sugars	$14M in revenue by 2016; $11M in sales in 2019
Ten Thirty One Productions	$3M annual sales up to 2018; acquired by 13th Floor Entertainment for an undisclosed amount
Tipsy Elves	$125M in sales by 2019
Tower Paddle Boards	$43M in sales by 2019
Wicked Good Cupcakes	$24M in sales by 2019
Xero Shoes	$1.5M in sales in 2015; $2.7M in sales in 2016; $5.1M in sales in 2017; $12.2M in sales in 2018

Table A3 (continued)

Panel A: Shark Tank Home Runs (continued)	
Source	URL
Primary sources:	
Associated Press News	https://apnews.com/acdb38364172477bb4e1518ea8261b38
CNBC	https://www.cnbc.com/2019/10/14/best-selling-shark-tank-products.html
Forbes	https://www.forbes.com/sites/alejandrocremades/2019/04/20/they-were-rejected-on-shark-tank-and-today-are-making-millions/?sh=3dea03ec3cde
Forbes	https://www.forbes.com/sites/susanadams/2016/03/18/ten-of-the-best-businesses-to-come-out-of-shark-tank/#87c28ae32bf0
Fortune	https://fortune.com/2017/09/12/successful-shark-tank-products/
USA Today	https://www.usatoday.com/story/life/tv/2018/10/05/shark-tank-top-20-products-abc-10th-season/1504708002/
USA Today	https://www.usatoday.com/story/entertainment/tv/2019/10/10/shark-tank-exclusive-new-list-20-best-selling-products/3841699002/
Other sources:	
Bustle	https://www.bustle.com/articles/49056-what-are-shark-tanks-most-successful-products-7-businesses-that-turned-out-to-be-great-investments
Bustle	https://www.bustle.com/p/16-shark-tank-products-that-are-now-so-successful-10224581
Considerable	https://www.considerable.com/entertainment/tv/shark-tank-most-memorable-products/
E! News (E! Online)	https://www.eonline.com/news/1125537/11-greatest-products-to-come-out-of-shark-tank
GoBankingRates	https://www.gobankingrates.com/money/business/most-successful-shark-tank-products/
Huffpost	https://www.huffpost.com/entry/9-most-successful-shark-t_b_6708126
Inc	https://www.inc.com/business-insider/most-succesful-shark-tank-companies-of-all-time.html
Investopedia	https://www.investopedia.com/articles/investing/082415/10-most-successful-products-shark-tank.asp
Kiplinger	https://www.kiplinger.com/slideshow/business/t049-s001-8-shark-tank-fails-that-turned-into-big-successes/index.html
Lovemoney	https://www.lovemoney.com/gallerylist/77588/american-shark-tank-success-stories-that-made-millions
Mentalfloss	https://www.mentalfloss.com/article/546955/shark-tank-most-successful-products
MoneyPPL	https://moneyppl.com/rejected-shark-tank-ideas-that-ultimately-found-success/21684/
ProductHype	https://blog.producthype.co/best-shark-tank-products/
Startup Mindset	https://startupmindset.com/here-are-the-15-best-investments-each-shark-has-made-on-shark-tank/
ThePioneerWoman	https://www.thepioneerwoman.com/news-entertainment/g32010989/best-shark-tank-products/?slide=1

Table A3 (continued)

Panel B: Startup Battlefield Home Runs (Source: Crunchbase, June 2021)	
Business	Comment
2600Hz	$50-100M in sales
AirHelp	501-1,000 employees
Carbon Health	$173M total funding amount raised
Discord	$479M total funding amount raised
Emburse	501-1,000 employees
Enigma Technologies	$130M total funding amount raised
Everlywell	$325M total funding amount raised
JumpCloud	$192M total funding amount raised
N26	$819M total funding amount raised; $50-100M in sales; 1,001- 5,000 employees
Osano	$50-100M in sales
Productboard	$137M total funding amount raised
Valor Water Analytics	$50-100M in sales

Table A4 Correlations among first impression measures of facial traits.

This table reports the correlation matrices of first impression measures of the entrepreneurs' facial traits for both the Shark Tank (Panel A) and Startup Battlefield (Panel B) samples. Each survey respondent's evaluation of every entrepreneur characteristic is normalized to zero mean and unit variance within the responses provided for all of the video stills evaluated by the same respondent. *** denotes statistical significance at the 1% level.

Panel A: Shark Tank sample

	Confidence	Trustworthiness	Ability to handle pressure	Attractiveness	Likability
Competence	0.775***	0.889***	0.903***	0.380***	0.387***
Confidence		0.722***	0.844***	0.534***	0.464***
Trustworthiness			0.800***	0.459***	0.645***
Ability to handle pressure				0.297***	0.331***
Attractiveness					0.580***

Panel B: Startup Battlefield sample

	Confidence	Trustworthiness	Ability to handle pressure	Attractiveness	Likability
Competence	0.789***	0.838***	0.882***	0.512***	0.577***
Confidence		0.647***	0.861***	0.627***	0.530***
Trustworthiness			0.753***	0.564***	0.756***
Ability to handle pressure				0.463***	0.494***
Attractiveness					0.748***

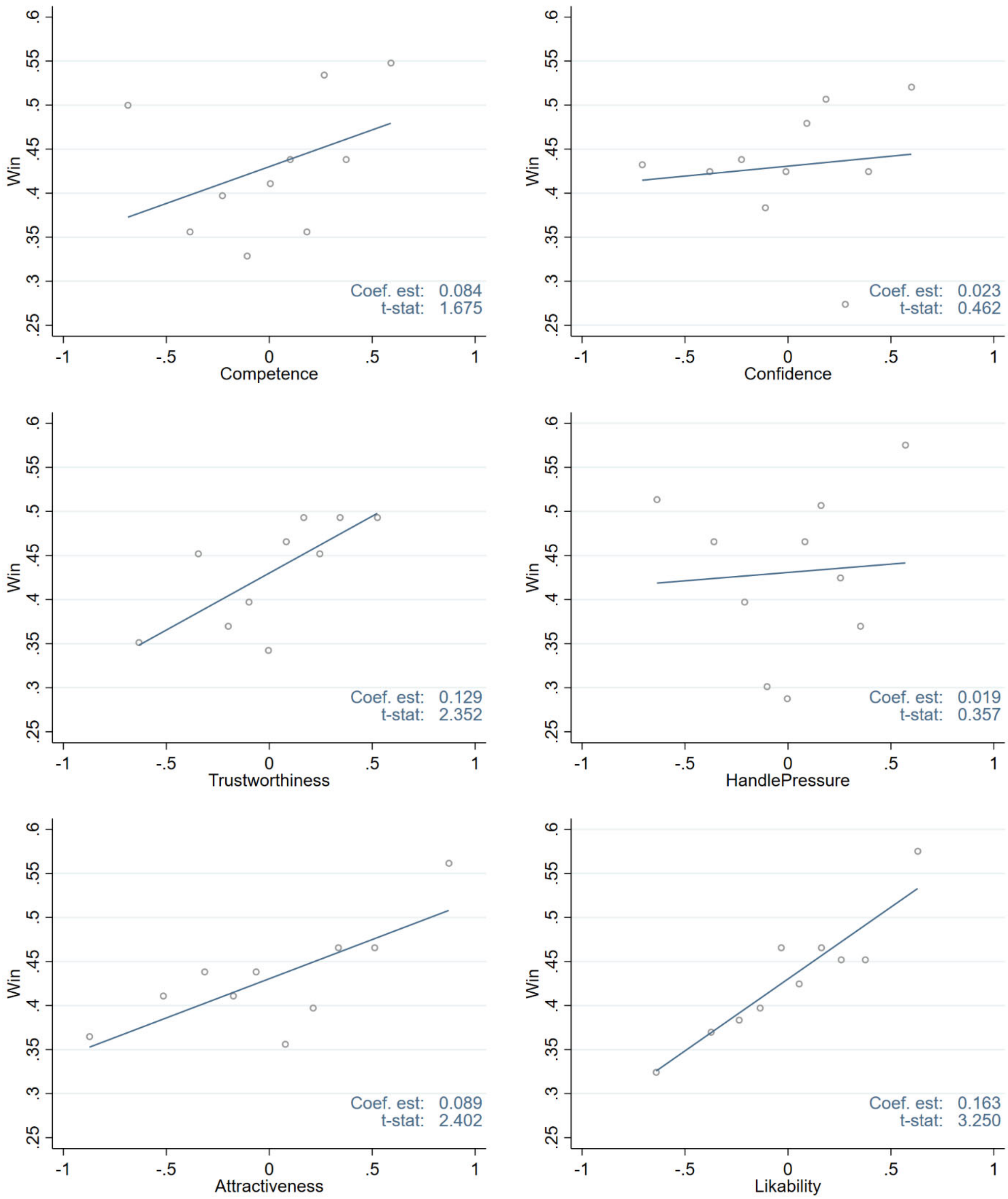

Fig. A1 Probability of winning (receiving an investment offer on Shark Tank or winning a competition round on Startup Battlefield).

For each of the six facial traits, the entrepreneurs (teams) are first sorted by the standardized scores of the first impressions collected from survey respondents and divided into deciles. The six figures present the binned scatterplots that display the average probabilities of winning (receiving an investment offer on Shark Tank or winning a competition round on Startup Battlefield) for the decile of each trait. Each figure features the linear probability fitted line and the corresponding regression statistics.