KU LEUVEN

KU Leuven, Faculty of Economics and Business
Dept. of Management, Strategy and Innovation (MSI)

The look of success:
AI-measured face factors and venture financing

Liudmila Alekseeva, Silvia Dalla Fontana, Caroline Genc and Lin Peng

MSI Discussion Paper No. 2507

The Look of Success: AI-Measured Face Factors and Venture Financing*

Liudmila Alekseeva, Silvia Dalla Fontana, Caroline Genc, and Lin Peng

August 2025

ABSTRACT

This study presents the first large-scale analysis of face-based impression factors in the venture capital (VC) industry. Using machine learning to extract key impression factors from founders' photos, we find that perceived trustworthiness, dominance, and youthfulness significantly predict VCs' initial funding decisions, with relative importance varying by founder gender, team composition, and industry. These factors also predict the funding amount, follow-on financing, and longer-term outcomes, such as unicorn status and acquisitions. Therefore, even experienced investors rely on facial cues when evaluating founders, and such cues serve as imperfect but informative signals of venture success.

Key words: venture capital, investment selection, impressions, facial recognition, trustworthiness, dominance, attractiveness.

JEL classification: G11, G24, G32, L26

*Liudmila Alekseeva: KU Leuven, ✉ liudmila.alekseeva@kuleuven.be. Silvia Dalla Fontana: ESCP Business School. ✉ sdallafontana@escp.eu. Caroline Genc: Eli Broad College of Business, Michigan State University. ✉ genccaro@msu.edu. Lin Peng: Zicklin School of Business, Baruch College, City University of New York. ✉ lin.peng@baruch.cuny.edu. We thank Veroniek Collewaert, Michael Ewens, Zoran Ivković, and the participants in the Workshop on Entrepreneurial Finance and Innovation Fellows Conference at Columbia University for valuable feedback, and Yukun Liu for excellent research assistance.

1 Introduction

Early-stage venture financing is characterized by a highly uncertain environment in which investors face significant informational constraints. Because hard information, such as traditional financial metrics and performance indicators, is generally unavailable for early-stage startups, investors often rely on soft information and intuitive judgments, their gut-feeling, to guide their investment decisions. Among the most immediate and influential sources of soft information are impressions formed from observing founders' facial characteristics. Supporting this idea, neuroscience and behavioral science research suggests that facial cues such as perceived trustworthiness, attractiveness, and dominance, can shape evaluative judgments within milliseconds, often outside conscious awareness (Schiller et al., 2009, Todorov, 2017).

This paper investigates the role of such impressions in the decision-making processes of venture capitalists (VCs), a critical group of professional investors that fosters innovation and drives economic growth (Gornall and Strebulaev, 2021). We conduct the first large-scale analysis of face-based impression factors (*face factors*) in the VC industry. Using machine learning techniques to analyze founders' facial characteristics, we examine whether and how these impressions influence VCs' investment decisions and the subsequent performance of funded ventures.

Our study is motivated by recent research that explores the effect of founder appearance and pitch delivery style on the investment decisions of angel investors and accelerator programs (Huang et al., 2023, Hu and Ma, 2025). These studies highlight the potential influence of impression factors in early-stage funding contexts.

However, unlike angels and accelerators, who may be more susceptible to subjective cues due to their informal or development orientation, VC firms operate under formal institutional structures. Angel investors generally invest their own capital via informal networks,

while accelerators offer startups short-term, intensive support, within a more experimental framework (Lerner et al., 2018, Cohen et al., 2019, Hellmann et al., 2021). In contrast, VC firms manage pooled funds, conduct rigorous due diligence, and actively engage with portfolio companies post-investment. They are also bound by fiduciary duties to protect their limited partners' (LPs) interests. These institutional features suggest that VCs should rely on systematic, data-driven evaluations rather than subjective cues. At the same time, VCs' investment decisions often occur under conditions of uncertainty and incomplete information, leaving room for instinctive judgments (Gompers et al., 2020).[1] Hence, it remains unclear whether founder appearance affects VC decisions and how these impressions shape venture outcomes.

To address this question, we construct a comprehensive dataset of U.S.-based startups and their founders. Drawing from Crunchbase, we compile information on 57,460 unique startups founded between 2012 and 2021, encompassing 74,137 distinct founders. The dataset includes detailed information on company and founder characteristics, as well as data on 2,498 investors, enabling us to control for a rich set of observables that may affect funding and performance outcomes.

We apply machine learning algorithms to founder profile photos to extract perceptual dimensions of face-based impression factors known to shape social judgments. We use a three-factor model identified in prior research (Oosterhof and Todorov, 2008, Vernon et al., 2014), consisting of trustworthiness (*Trust*), dominance (*Dom*), and youthfulness/attractiveness (*YoAt*). These dimensions serve as proxies for perceived approachability, strength/confidence/

[1] Anecdotal evidence from Masayoshi Son, founder of SoftBank, illustrates the role of instinct in VC decision-making: "He had no business plan, zero revenue," Son said of Jack Ma during an interview on The David Rubenstein Show. "But his eyes were very strong. I could tell from the way he talked, he has charisma, he has leadership" (Alpeyev, 2020). Similarly, Charles Hudson, managing partner at Precursor Ventures, noted that at the pre-seed stage, "there's not much for a VC to analyze—no revenue curve, no retention metrics, no CAC. That doesn't mean they're guessing. It means they're watching everything else" (TechCrunch Events, 2025).

assertiveness, and youthfulness/attractiveness, respectively. Cognitive psychology research suggests that this three-factor structure accounts for a wide range of trait impressions, explaining roughly 72% of the variation in first impressions formed from observing faces (Oosterhof and Todorov, 2008, Sutherland et al., 2013).

We first examine whether the face factors influence the likelihood of securing VC financing. We find that, after controlling for a rich set of observable firm-level and founder-level characteristics, all three factors are significantly associated with the probability of receiving VC financing. Compared to other founder characteristics traditionally considered in VC financing decisions, face factors demonstrate comparable, and in some cases stronger, predictive power, both in terms of coefficient magnitude and statistical significance. Among these traits, *Trust* emerges as the most robust and economically meaningful predictor of VC financing: a one standard deviation increase in perceived founding team trustworthiness is associated with a 1.17 percentage point increase in the likelihood of receiving VC funding, an approximate 6.9% increase relative to the unconditional probability. Similarly, the corresponding increases in perceived dominance and attractiveness are associated with a higher likelihood of funding by 0.43, and 0.35 percentage points, respectively.[2]

There are significant heterogeneities in the relative importance of the face factors in predicting VC decisions, shaped by startup characteristics such as gender composition, size of the founding team, and industry. For example, face factors tend to play a larger role in the instances in which the team has a mixed-gender structure and the startup is founded by a team rather than a solo entrepreneur. Specifically, *Trust* consistently predicts VC funding

[2]By comparison, a one standard deviation increase in the average educational background of the team, measured by the share of members with Ph.D. or STEM degrees, raises funding likelihood by 0.97 and 1.20 percentage points, respectively, while the share of MBA or Master's degrees has no significant effect. In terms of prior experience, a one standard deviation increase in the share of team members with the CEO, C-Suite, investor, or top employer experience increases funding likelihood by 0.83, 1.08, 2.16, and 1.48 percentage points, respectively.

for all-male and mixed-gender founding teams, but not for all-female teams.[3] Similarly, *Dom* is a key predictor for teams that include males (all-male and mixed-gender) and have multiple founders but does not predict funding for solo founders or all-female teams. Because *Dom* captures assertiveness and authority, it might be especially relevant in multi-founder teams in which investors assess internal group dynamics. In such settings, *Dom* can help identify who might lead, negotiate, or perform under pressure. For solo founders, however, this trait is less informative because the founder is, by default, the leader. Finally, *YoAt* has a particularly strong association with funding decisions for multi-founder and mixed-gender teams but is a weaker predictor of financing in female-only and male-only teams.

Industry-level analysis reveals additional heterogeneities. *Trust* emerges as a broadly influential trait, particularly in the sectors in which trustworthiness and perceived reliability are critical to success. However, its predictive power diminishes in the Healthcare sector, where the average founder *Trust* level is already high. This suggests that when a facial trait is widely prevalent within an industry, it becomes less informative for VCs as a differentiating signal and does not always translate into a financing advantage. Similarly, while *YoAt* is insignificant for Consumer Products and Services, where the industry average is the highest, it is significant for Healthcare. *Dom*, for which founders in Biotech and Hardware tend to have a high score on average, is not significantly associated with VC financing in these sectors. It significantly predicts VC financing in Financial Services and Healthcare, possibly reflecting some reliance on stereotypes of confidence and strength in these industries.

Taken together, these results suggest that VCs may rely, at least partially, on intuitive judgments based on facial cues when making investment decisions. This raises a fundamental

[3]Consistent with psychology research (e.g. Olivola and Todorov, 2010, Oh et al., 2019), we find that, on average, female founders are perceived as more trustworthy and more youthful/attractive than their male counterparts. Because these traits are more commonly observed among women, they may carry less informational value for investors evaluating female-led ventures.

question: whether this reliance on face factors is rational, and whether it aligns with venture performance outcomes.

If VCs' reliance on facial cues reflects judgment errors during initial encounters, the influence of face factors would likely diminish over time. As VCs interact more extensively with founders post-financing, the relation between face factors and venture success would fade or even reverse in the long run. However, if facial cues are part of a rational decision-making process aligned with long-run performance, the predictive power of face factors would likely persist over longer horizons.

To differentiate between these two hypotheses, we examine a range of post-investment outcomes, including the amounts of capital raised, the likelihood of securing follow-on financing, the attainment of high valuation milestones (e.g., unicorn status), and eventual exit events. Our findings are consistent with the rational behavior hypothesis: face factors continue to play a significant role beyond the first round of financing. All three factors remain positively associated with the likelihood of securing a second round of funding. This persistence suggests that face factors may serve as lasting signals of competence or leadership potential.

Dom emerges as the strongest predictor of the amount of VC capital raised, initially and across all rounds. This indicates that dominant-looking founders not only may inspire greater investor confidence in their firms' potential but may also negotiate more effectively. In contrast, *Trust* and *YoAt* have no significant effect on investment size once funding is secured. These findings suggest that, whereas perceived trustworthiness and youthfulness/attractiveness are important during initial selection, perceived dominance becomes more relevant in shaping the scale of investor commitment.

We further explore a particularly meaningful venture outcome: reaching unicorn status,

a benchmark often used in venture capital to indicate exceptional growth potential.[4] Given VCs' focus on identifying "home runs" that deliver outsized returns and offset the high failure rate of early-stage investments, becoming a unicorn represents a particularly relevant success outcome. We find that *YoAt* is the only facial trait significantly associated with the likelihood of reaching unicorn status.[5]

Finally, we examine successful exit events such as IPOs and acquisitions. *Trust* and *Dom*, both of which predict VC financing, also emerge as significant predictors of exit outcomes, with the effects mostly driven by acquisitions. Focusing solely on non-VC-backed startups, we also investigate whether the face factors are able to predict venture outcomes independent from VC involvement. We find that *Trust*, the most robust predictor of VC financing, is also a broadly relevant signal of venture success even in the absence of VC involvement. Combined with earlier findings, these results suggest that, while VCs' reliance on facial appearance may appear superficial, such reliance may capture subtle cues that predict meaningful entrepreneurial outcomes.

A caveat is that we cannot rule out the possibility that these findings reflect a self-fulfilling prophecy of an investment-success dynamic. Because VCs play an influential role in shaping entrepreneurial trajectories, their initial judgments could themselves contribute to venture success, creating feedback loops where even biased perceptions yield favorable outcomes. Nevertheless, the absence of systematically poorer outcomes for teams with preferred facial

[4] A *unicorn* refers to a privately held startup valued at over $1 billion, a milestone often used in venture capital to signal exceptional growth potential, investor confidence and market impact.

[5] Neither trustworthiness nor dominance significantly predicts unicorn attainment. It is unclear why these two dimensions, which matter earlier in the financing process, do not translate into predicting the most extreme success outcomes. One possibility is that once a firm has passed early financing hurdles, later-stage growth depends more on external partnerships, customer adoption, and visibility, where youthful and attractive impressions may be especially advantageous. Another possibility is that trust and dominance may be screened by VCs earlier in the process, leaving limited variation among firms that survive to later stages. Ultimately, why only youthfulness/attractiveness predicts unicorn attainment remains an open question, pointing to the need for future research.

traits suggests that such reliance, even if shaped by norms or stereotypes, may be rational within the institutional environment in which VCs operate.

Our study contributes to several strands of literature. A growing body of research in economics, finance, and accounting highlights the importance of face-based inferences for individual-level outcomes.[6] More recent studies focus on firm-level outcomes. Closely related to our paper, Huang et al. (2023) show that angel investors are highly responsive to founders' facial traits in televised competitions, while Hu and Ma (2025) find that delivery style and expressiveness in accelerator video pitches significantly increase financing likelihood. Together, these studies demonstrate that nonverbal cues systematically shape early-stage investment outcomes.[7]

However, several important distinctions set our paper apart. First, we focus on venture capitalists, who differ fundamentally from angel investors or accelerators in organizational structure, fiduciary obligations, and post-investment involvement. Their decisions also carry greater economic weight given the scale of their capital commitments and influence on portfolio companies.[8]

Second, whereas previous studies suggest that reliance on impression factors by angel investors or accelerators may reflect poor judgment, we find that VCs' reliance on face

[6]Attractiveness is linked to more favorable judicial rulings (Zebrowitz and McDonald, 1991) and higher wages (Mobius and Rosenblat, 2006). Perceived trustworthiness affects political election outcomes (Todorov et al., 2005), corporate advancement (Linke et al., 2016), loan terms (Duarte et al., 2012), and auditor tenure (Hsieh et al., 2020). Perceived competence is associated with CEO compensation (Graham et al., 2017), whereas analysts' facial features predict performance, career progression (He et al., 2019, Cao et al., 2020, Li et al., 2020, Peng et al., 2022), and financial misreporting (Jia et al., 2014). Moreover, face-based personality traits have been found to predict labor market outcomes among MBA graduates (Guenzel et al., 2025).

[7]In a crowdfunding setting, Duan et al. (2020) show that entrepreneurs' facial trustworthiness is positively associated with campaign success. Blankespoor et al. (2017) construct a composite measure of investor perception from 30-second IPO roadshow videos and find that it is positively associated with pricing.

[8]The VC market is substantially larger, projected to reach $1.41 trillion in 2025 (Mordor Intelligence, 2025), compared to the startup accelerator market, valued at $1.9 billion in 2024 (Market.us, 2025). See: `https://www.mordorintelligence.com/industry-reports/united-states-venture-capital-market`, and `https://market.us/report/startup-accelerator-market/`.

factors aligns more consistently with better outcomes. For instance, unlike the evidence associated with accelerator programs (Hu and Ma, 2025), we do not find that VCs' reliance on face factors results in systematically poorer performance.[9] Relatedly, whereas Huang et al. (2023) show that angels sometimes irrationally favor charm over competence, we find that *YoAt*, plausibly linked to charm, is positively correlated with the success metrics that VCs prioritize. Institutional differences between VCs, angels, and accelerators may explain why reliance on facial cues appears more performance-enhancing in the VC context.

Third, the scale of our analysis – considerably larger than related studies – enables us to provide many novel insights into how startup and founding team characteristics, such as industry, team composition, and gender structure interact with face factors to influence funding outcomes, while controlling for a rich set of covariates.[10] These results highlight important heterogeneity in the role of face impressions across contexts.

Finally, these findings broaden the understanding of what founder and CEO characteristics matter for success. Whereas prior research has emphasized financial and managerial skills (Kaplan and Strömberg, 2000, Kaplan and Stromberg, 2004, Kaplan et al., 2009, Bernstein et al., 2017, Gompers et al., 2020, Gonzalez-Uribe et al., 2023), we show that perceptual traits, such as facial cues, also play an important role in shaping investment decisions and firm outcomes.

[9]While we find that all face factors predict financing, *Trust* and *Dom* are also positively associated with M&A exit outcomes, whereas *YoAt* predicts unicorn status.

[10]Our final sample includes 57,460 startups, 74,137 distinct founders, and 2,498 investors. By comparison, Hu and Ma (2025) examine 1,139 startup founders, Hu and Ma (2025) study 379 entrepreneurs, and Blankespoor et al. (2017) analyze 224 CEOs of IPO firms.

2 Data

This section outlines our primary data source, provides the details of the sample construction process, explains the development of key measures, and presents descriptive statistics.

2.1 Startup and VC Financing Data

In this subsection, we provide an overview of our primary dataset, Crunchbase, and describe the procedures used to construct our sample.

2.1.1 Overview of Crunchbase data

Our primary dataset is derived from Crunchbase, one of the most comprehensive and widely used commercial databases for startup-related information and venture capital investments. Several studies have validated the accuracy of Crunchbase data, particularly for U.S.-based startups, and it has become an increasingly prominent data source in academic research (Dalle et al., 2017, Retterath and Braun, 2020). A distinctive advantage of Crunchbase over traditional venture capital databases (e.g., Pitchbook, VentureXpert, Venture Source, AngelList) lies in its broader coverage: it includes not only VC-backed firms but also startups that have not at all, or not yet, raised external financing. Moreover, Crunchbase provides comprehensive coverage of both private and public ventures, including detailed profiles of founders, employees, and investors. These features are particularly valuable for our analysis because they offer a representative view of the high-growth entrepreneurial landscape. The data structure simplifies founder identification and, crucially, grants access to profile images. These images are essential for extracting face factors, a key ingredient of our study.

The platform may exhibit some bias toward companies actively seeking funding because

of its user-contributed and investor-oriented nature. This bias, to whatever extent it may be present, if anything, is advantageous for our purposes. Our study aims to examine VC investment behavior, which necessitates a pool of non-VC-backed companies that are still entrepreneurial in nature and are plausibly in the process of, or inclined toward, seeking external funding. Therefore, Crunchbase is particularly well-suited for our study.

2.1.2 Sample construction

We describe our sample construction, which is also summarized in Appendix Table A3. From the full set of over 3.7 million organizations exported from Crunchbase in January 2025, we retain for-profit companies with available founding year, industry classification, country of location, and at least one identified founder, excluding records with incoherent temporal data such as exits preceding founding dates or IPOs after closure. This yields 656,219 unique companies (17.5% of the original dataset) and 950,963 company-founder observations.[11]

We then focus on U.S.-based startups and investors, producing 350,305 founder-organization pairs, and restrict the sample to startups founded between 2012 and 2021, resulting in 153,895 founder-company pairs. These temporal bounds ensure sufficient post-founding time to observe VC rounds and reduce photo-to-founding lags in face-factor measurement. After these filters, the dataset covers 90,936 companies, including VC-backed and non-financed firms, with VC rounds identified by funding stage and investor type. Finally, we require usable founder photographs for the majority of the founding team, i.e., images of sufficient quality to extract facial features.[12]

[11] The requirement for detailed company information removes 29% of the observations, and the founder requirement eliminates a further 75% of the remainder.

[12] Investors often discover founders through digital platforms such as Crunchbase or LinkedIn, which serve as modern resumes; profile photos thus provide a standardized first point of visual contact. These images are typically curated to professional norms, ensuring reliability for analysis. While we cannot verify that Crunchbase directly sources photos from LinkedIn, the two platforms have partnered on profile integration since 2018 (see: `https://about.crunchbase.com/blog/crunchbase-insights-linkedin-pages/`.)

Our final sample consists of 80,198 company-founder observations from 57,460 startups and 74,137 distinct founders, with VC-backed startups representing 17% of all startups and the remainder having no recorded external financing. The percentage of VC-backed startups is higher than the commonly cited figure of less than 1% among all new U.S. businesses (Puri and Zarutskie, 2012), reflecting our focus on high-growth startups actively seeking venture capital.

Our Crunchbase data provide extensive information on companies (e.g., founding date, detailed industries, location, amount of financing raised, if any, characteristics of participating investors and details of financing rounds, as well as performance indicators) and founders (founding team size, gender, founder's prior entrepreneurial/CEO experience, education history). These rich features allow us to control for a broad set of observable characteristics and more precisely evaluate the relation between the founder face factors and both startup fundraising and performance. For our main regression analyses, we aggregate founder-level characteristics to the company level by averaging each variable across all founders within a given firm.

2.2 Face Factors

Existing research shows that impressions based on face attributes affect a wide range of social outcomes, including political elections (Todorov et al., 2005), legal sentencing decisions (Jaeger et al., 2020), dissemination of scientific research (Gheorghiu et al., 2017), and labor market outcomes (Goldin and Rouse, 2000). Findings show that similar effects of impressions exist in finance-related contexts, influencing financial analysts' forecast accuracy (Peng et al., 2022, Cao et al., 2020), firms' valuation at IPO (Blankespoor et al., 2017), and angel investors' and accelerators' decisions (Huang et al., 2023, Hu and Ma, 2025). These findings suggest that facial cues can sometimes align with decision quality, for example, analysts

with more favorable facial impressions deliver more accurate forecasts, and managers with such impressions obtain higher IPO valuations. At the same time, however, other studies caution that over-reliance on appearance can lead to worse decision outcomes (Olivola and Todorov, 2010).[13] Given the venture capital industry's strong reliance on soft information, subjective factors such as impressions formed from a founder's facial appearance may also influence investment decisions. We use founder profile pictures to estimate three face factors that capture key dimensions of how individuals are perceived. These include trustworthiness (*Trust*) and dominance (*Dom*) proposed in the seminal paper by Oosterhof and Todorov (2008), along with an attractiveness (*YoAT*) factor later introduced by Sutherland et al. (2013). Vernon et al. (2014) show that these three dimensions account for a substantial share of the variance in impressions formed from facial cues. Trustworthiness typically reflects perceived approachability and the likelihood that the individual has good intentions. Dominance captures impressions of strength, confidence, and assertiveness. Attractiveness, in this context, is closely associated with perceived youthfulness because younger individuals are generally rated as more attractive.

To estimate the founders' face factors, we follow Peng et al. (2022). First, we preprocess founders' profile photos obtained from Crunchbase to standardize their size and head location. Second, we apply the IBUG facial recognition software to all the photos. IBUG constructs 65 physical face features attributes, from which we calculate the raw factor scores using the weights in Vernon et al. (2014) machine learning model.[14] Finally, we standardize all the raw face factors to range between -1 and 1.

[13] Olivola and Todorov (2010) showed that people generate less accurate predictions about persons' characteristics when they account for appearance than they would be if they ignored appearance cues.

[14] Vernon et al. (2014) proposes a quantitative model that can predict impressions based on face images.

2.3 Descriptive Statistics

2.3.1 Final Sample Description

Table 1 presents descriptive statistics for the firm-level data used in the regression analysis.[15] Panel A reports company characteristics for our main regression sample of 57,460 unique U.S. startups. It shows that, whereas 69% of the companies are solo-founded, the average number of founders is 1.46. Among the founders, 23% of the firms include at least one female. Almost one-third of the companies are located in California. About 7% of the firms in our sample achieved an IPO or an M&A exit.[16] Acquisition exits are the dominant type, with 6% of the companies achieving such an exit, while IPOs are relatively rare with fewer than 1% of the companies going public. Around 17% of the firms have obtained VC financing and, conditional on being VC-backed, and 59% reached a second round. Lastly, the average financing round involves almost $9 million of financing. Because our focus is on the first VC rounds, our sample covers mainly early and seed stage financing.[17]

Panel B reports average founder characteristics at the team level. The average age of founders at the time of company founding is 31.39 years, based on either direct data or estimates derived from educational and professional histories. At founding, the average within-team educational composition includes 90% with at least a Bachelor's degree, 28% with a Master's, 11% with a Ph.D., and 14% with an MBA. On average, 35% of team mem-

[15] Descriptive statistics at the founder level are reported in Appendix Table A2.

[16] The exit rates in our overall sample are lower than those reported in the studies analyzing VC-backed companies (e.g., Ewens and Farre-Mensa, 2020) because our sample includes relatively young firms (we observe exits until the end of 2024 for the sample of companies founded between 2012 and 2021) and because it includes companies without any reported financing, typically characterized by lower exit rates compared to VC-backed startups. Exit rates in the VC-backed subsample align with the literature.

[17] Tables A5 and A6 show the distribution of companies across Crunchbase industry groups and their more aggregate categories (described in Table A7). Our sample consists of Software companies (36%), Information Technology (19%), Professional Services (18%), Internet Services (17%), Healthcare (15%), Media and Entertainment (15%), Sales and Marketing (15%).

bers have a STEM background, and 17% hold degrees from elite institutions.[18] Education information is available for 51% of the founder teams in our sample. We take this paucity of education information into account by controlling for a missing education variable. In terms of professional background, founder teams have an average of 3.8 years of prior work experience in one job listed on Crunchbase; 31% of founders had previously founded a company, 14% served as a CEO, and 14% held a "Chief" title. Experience in top-tier firms or as investors is relatively rare, each observed in 3% and 2% of the sample, respectively.

2.3.2 Sample Selection

To assess potential selection biases introduced by the face factors availability, Table A4 compares company and founder characteristics in our final sample with those in the broader sample constructed without the photo availability requirement. About 65% of the companies have founders with available photos. While most differences in firm-level and founder-level characteristics across the two samples are statistically significant, they are generally not substantial in magnitude.

Founding teams in the final sample are slightly larger on average (1.86 vs 1.83 members), and the proportion of female-founded firms is modestly higher (0.248 vs 0.217). Differences in founder characteristics are mainly related to experience, which aligns with the observed age gap: founding team members in the final sample are, on average, half a year older and have half a year more work experience. Educational attainment is broadly similar across samples, with differences in degree types (e.g., MBA, Ph.D., STEM) generally below one percentage point. Founding teams in the final sample are 1.2% more likely to have members who graduated from elite institutions.

Overall, while statistically detectable, these differences are limited in practical significance

[18] Elite Institutions are defined following Gompers et al. (2016) and Amornsiripanitch et al. (2022).

and suggest broadly comparable profiles across the two groups.

3 Empirical Design

Our empirical analysis aims to assess whether, conditional on a large set of observable founder and startup characteristics, VCs are influenced by impression factors based on founders' facial characteristics, and whether such impressions lead to irrational decisions. In this section, we outline the empirical methodology we use to address these questions.

We first analyze the relation between the likelihood of securing VC financing and face factors *Trust*, *Dom*, and *YoAt*. These factors are constructed at the founder level and aggregated to the startup level using team averages. This aggregation captures the overall profile of the founding team as perceived by investors, serving as a proxy for the information available during early-stage evaluations. In practice, early-stage evaluations often rely on online platforms (e.g., LinkedIn or Crunchbase) or pitch materials, where investors may form impressions based on profile pictures and brief biographical summaries before any direct interaction occurs. By aggregating face factors, our approach mirrors these real-world conditions under which face-based impressions are likely to influence decision-making.

We then extend our analysis beyond the initial investment stage to examine several post-investment outcomes. If face factors are positively associated with future success, VCs either rely on valid heuristics when making funding decisions, or reinforcement mechanisms, such as self-fulfilling or feedback effects, lead to favorable outcomes despite potentially biased perceptions. However, if these impressions do not correlate, or negatively correlate, with performance outcomes, VCs may be irrationally influenced by biased judgments.

Hence, in addition to the amount raised in the first round and the total equity amount raised, we analyze three key indicators of startup success: (1) the probability of raising

a second round of financing, (2) the likelihood of achieving unicorn status, and (3) the probability of a successful exit, defined as an IPO or an M&A. Together, these outcomes provide a comprehensive view of both short-term and long-term performance, allowing us to evaluate whether initial face-based impressions are mainly superficial cues or whether they reflect deeper signals of entrepreneurial potential.

We estimate a series of linear probability models to examine the relations between key investment and performance outcomes and face factors. The baseline specification is:

$$Outcome_i = \beta Face\ Factors_i + \gamma X_i + \delta_{ind(i)} + \lambda_{s(i)\times t(i)} + \varepsilon_i, \tag{1}$$

where $Outcome_i$ denotes the outcome variable of interest for startup i. The outcome variables include an indicator variable that takes the value of one if firm i raised VC financing, achieved a successful exit (IPO or M&A exit), raised a second round of funding conditional on obtaining VC financing, reached the unicorn status, and the logarithm of the amount raised in the first round and across all rounds. *Face Factors* correspond to the three face factors described in Section 2.2 constructed at the founder level and aggregated at the firm level using averages.

The vector of controls X_i captures founder and firm characteristics that might influence startup outcomes and investor decisions: an indicator for female-founded firms, founding team size, and a detailed set of founder-level attributes aggregated at the company level, including founder age, years of overall work experience, prior experience as a founder, C-suite, CEO, "chief" employee, or investor roles, experience at top-tier employers, educational attainment (MBA, Master's, Ph.D., or STEM degree), elite school credentials, and an indicator for missing education data. Our specification also incorporates founding year × state

($\lambda_{s(i)\times t(i)}$), and industry fixed effects ($\delta_{ind(i)}$).[19] The fixed effects absorb systematic differences in startup fundraising and outcomes that may arise from regulatory or macroeconomic shocks affecting specific cohorts and regional entrepreneurial ecosystems, as well as persistent cross-industry variation in financing. By including these fixed effects, we ensure that the estimated relation between face factors and venture outcomes is not confounded by variation driven by geography, timing, or industry context.

4 Face Factors and the Likelihood of VC Financing

To investigate whether and how face factors influence VCs' investment decisions, we begin by presenting a baseline analysis of the relation between the likelihood of securing VC financing and face factors. We then explore how this relation is shaped by the gender composition and size of the founding team, as well as the startup's industry.

4.1 Baseline Analysis

Figure 1 compares the average face factors between founders of VC-backed and non-VC-backed startups. It reveals that these groups differ across all three face factors: *Trust* and *Dom* are generally higher, and *YoAt* is lower, for VC-backed companies. This first descriptive result suggests that perceived facial characteristics may play a role in shaping VCs' investment decisions.

To examine the relation between the likelihood of receiving VC financing and face factors more rigorously, we estimate regression models as specified in equation 1 and report the corresponding results in Table 2. Columns (1) through (3) show that all three traits are significant predictors of VC financing outcomes, each positively associated with the probability

[19] We use the set of indicator variables for detailed industry groups provided by Crunchbase, listed in Table A5, as industry fixed effects in baseline specifications.

of obtaining VC funding. Columns (2) and (3) further show that the results are robust to the inclusion of founding year × state fixed effects and industry fixed effects.

The face factor effects are not only statistically significant but also economically meaningful. Based on the coefficient estimates from column (3), a one standard deviation increase in perceived founding team trustworthiness is associated with a 1.17 percentage point increase in the likelihood of receiving VC funding, a relative increase of approximately 6.9% given the unconditional probability. The effects of *Dom* and *YoAt* are more modest but still significant, corresponding to increases of 0.43 and 0.35 percentage points, respectively, in the probability of raising VC financing.

The economic effects of face-based factors are comparable to, and in some cases larger than, those of key measurable characteristics traditionally considered in VC financing decisions. For instance, a one standard deviation increase in the average educational background of the founding team, measured by the share of members with Ph.D. or STEM degrees, raises funding likelihood by 0.97 and 1.20 percentage points, respectively, whereas holding an MBA or a Master's degree has no significant effect. Similarly, a one standard deviation increase in prior experience as a CEO, C-suite executive, investor, or employee at a top firm increases funding likelihood by 0.83, 1.08, 2.16, and 1.48 percentage points, respectively. In contrast, a comparable increase in age reduces funding likelihood by 1.64 percentage points. Founding teams whose members graduated from elite universities benefit from a significantly higher likelihood of securing funding, with an estimated increase of 3.14 percentage points. Conversely, a one standard deviation increase in the presence of female founders is associated with a 0.67 percentage points decrease in the funding likelihood.

We conduct several additional tests to assess the robustness of our findings. First, we exclude teams with ethnically diverse (non-white) founders to account for potential differences

in how appearance is evaluated (Appendix Table A8). The results remain both statistically and economically robust. Second, we restrict the sample of VC-backed startups to those listed on Crunchbase prior to the announcement of their first financing round, mitigating concerns that company profiles were added post-investment (Appendix Table A9). Again, the results are consistent.

Finally, we replace continuous face factor variables with indicator variables for above-median, bottom-quartile, and top-quartile values and re-estimate the regressions (Appendix Table A10). This approach allows us to detect potential non-linearities and threshold effects. The results reveal a monotonic relation between *Trust* and VC financing: teams with above-median or top-quartile *Trust* scores are significantly more likely to receive funding, whereas those in the bottom quartile are less likely, reinforcing the positive association observed in the specifications using continuous measures. For *Dom*, the pattern is different: above-median teams are more likely to be funded, and bottom quartile teams less so, but the effect becomes statistically insignificant at the top of the distribution. This suggests that there might be a plateau effect regarding *Dom*. *YoAt* exhibits a non-linear relation: teams in both the lowest and highest quartiles are less likely to secure financing, whereas having an above-median *YoAt* has no significant effect, indicating that extreme values of this trait may be penalized by investors.

These findings highlight the significant role of face-based impression factors in VC financing, even after accounting for observable characteristics. Therefore, founders' facial attributes may convey meaningful cues that VCs subconsciously or intuitively rely on when making investment decisions.

4.2 The Role of Founding Team Composition

As documented in the psychology literature (e.g., Olivola and Todorov, 2010, Oh et al., 2019), there are significant gender-based differences in face-based impressions. Figure 2 aligns with this evidence. It shows that female founders are, on average, perceived as more trustworthy and more youthful/attractive compared to their male counterparts. In contrast, male founders tend to be perceived as more dominant.

These differences raise the questions about how the gender composition of founding teams contributes to the results observed in the main analysis, and whether VCs respond differently to face factors depending on whether a company is female-founded, male-founded, or has a mixed-gender team.

To address these questions, we repeat our main analysis in the subsamples of (i) fully male-founded firms, (ii) mixed-gender founding teams, and (iii) fully female-founded firms. Table 3 presents the corresponding results. Columns (1) to (3) show that restricting the sample to male-only firms eliminates the positive and significant association between *YoAt* and VC financing, indicating that the result observed in the full sample is primarily driven by teams that include women. In contrast, the effects of *Trust* and *Dom* remain robust and statistically significant in this subsample. Columns (4) to (6) present the results for mixed-gender teams. All three face factors have positive and statistically significant coefficients, in line with the results observed in the full sample. Finally, columns (7) to (9) report the results for female-only companies, a setting in which none of the face factors are significantly associated with VC financing.[20]

[20]Table A11 presents the same analysis using interaction terms rather than subsample splits. The interaction results show that the coefficient of *Trust* differs significantly between male-only firms and both mixed-gender and female-only teams. The coefficients of *YoAt* and *Dom* differ between male-only and mixed-gender firms but not between male-only and female-only companies. For clarity, we report subsample analyses in the main text to directly illustrate the predictive power of face factors within each group of

Whereas our finding that female founders are less likely to receive VC funding is broadly consistent with prior work on gender-based disparities in entrepreneurial finance (Ewens and Townsend, 2020, Hebert, 2020), several differences emerge. For instance, Hu and Ma (2025) show that women in single-gender teams are judged more heavily on pitch delivery, while women in mixed-gender teams are often overlooked. In crowdfunding, perceived trustworthiness is a stronger predictor of financing for female than for male entrepreneurs (Duan et al., 2020). By contrast, in the VC setting, we find that face factors are not significant predictors of financing for all-female companies, suggesting that VCs may apply different evaluative criteria or place less weight on facial characteristics when assessing female-only ventures. Our finding therefore complements prior evidence on the gendered nature of investor evaluations by highlighting how the role of facial impressions varies across contexts and funding environments.[21]

Comparing the results for female-only companies with those from the other two subsamples, our findings suggest that VCs are more influenced by impressions related to youthfulness and attractiveness in mixed-gender founding teams, rather than all-female teams. Thus, gender not only shapes how founders are perceived, but may also condition the extent to which visual cues influence investor decision-making.

We further investigate whether the founding team structure influences how VCs respond to face factors because VCs may evaluate solo founders differently from multi-founder teams.[22] To this end, we split our initial sample into solo founders and multi-founder teams

companies.

[21]The lack of significance in our setting is not driven by lower variation in facial factors within the female-only subsample, as their variances are comparable to those in the rest of the sample. Results remain unchanged when limited to multi-founder teams (about 10% of female-founded firms).

[22]Tamaseb (2021) highlights that, in practice, investors tend to favor multi-founder teams over solo founders, largely because teams are perceived to bring broader expertise, complementary skills, and greater resource-mobilization capacity. The perception of teams as a stronger signal of venture quality is sufficiently widespread that founder matchmaking services have grown in popularity. Consistent with this view, in our sample, the likelihood of obtaining VC financing is 36% for team-founded startups, compared to only 8% for

and report our findings in Table 4. Columns (1) to (3) show that, after controlling for founder characteristics and fixed effects, *Trust* is the only facial trait significantly associated with VC financing in the sample of solo founders. Unreported analyses excluding female founders from this group show similar results. Columns (4) to (6) confirm that all three face factors matter for multi-founder teams' access to VC financing, with *Trust* having the strongest and most robust association across specifications.[23] These findings mirror those observed in the full sample and in mixed-gender team analysis, reinforcing the idea that face factors are more influential when investors evaluate founders in a comparative or team-based context.

Together with the gender-based findings, these results suggest that the influence of face factors is highly context-dependent. They appear to matter more when founders are evaluated in relation to others (across genders or within a team) than when assessed in isolation.

Specifically, trustworthiness emerges as the most important factor in all cases except for fully female-founded firms. Because the average *Trust* is relatively higher for female founders compared to male founders, it may be a less distinctive or informative signal when investors evaluate female-founded ventures. This interpretation is consistent with evidence from the psychology literature on visual search, showing that it is more difficult to distinguish a target when it is surrounded by similar distractors (e.g., Duncan and Humphreys, 1989, Wolfe, 2000). Analogously, when most female founders are perceived as at least moderately trustworthy, identifying those who are less or more trustworthy becomes more cognitively demanding. As a result, trustworthiness may offer limited discriminatory power in this context and thus be discounted by investors.

At the same time, dominance appears to be primarily important for multi-founder firms

those with a solo founder.

[23] Appendix Table A12 confirm the observed differences between solo founders and multi-founder teams using interactions. Appendix Table A13 presents results similar to columns (4) to (6) of Table 4 when using the maximum value of each face factor within founding teams rather than team averages.

and those with male founders, whereas it does not play a significant role for solo founders or all-female firms. The perceived assertiveness or authority conveyed by dominant facial features may be more relevant in group dynamics, in which investors implicitly evaluate leadership roles and internal hierarchies. In multi-founder settings, dominance might help signal who is likely to take charge, negotiate, or lead under pressure, making it a valuable cue for VCs when assessing team effectiveness. In contrast, for solo founders, dominance may be less informative, because there is no internal team dynamic to navigate and the founder is, by default, the leader.

Youthfulness and attractiveness of founders also appears to play a more important role for multi-founder and mixed-gender teams. In female-only firms, in which *YoAt* is also the highest, this result may again reflect the cognitive difficulty of distinguishing among similar-looking individuals, consistent with findings on visual search among homogeneous alternatives (e.g., Duncan and Humphreys, 1989).

4.3 The Role of Startup Industry

Figure 3 provides an initial overview of the variation of face factors across industries. It displays the average values of the three face factors for each of the broad industry categories, computed at the startup level and aggregated by industry. Panel A shows that the average *Trust* factor is particularly high in Healthcare and in the Other category including smaller sectors such as Professional Services, Media, and Education categories, among others. This suggests that founders starting companies in these industries tend to be perceived as more trustworthy based on facial cues, potentially reflecting sector-specific expectations around credibility, empathy, or social responsibility. This is consistent with existing evidence on the importance of trust in sectors that rely heavily on personal interaction and relationship building, such as service-based industries (e.g., Sirdeshmukh et al., 2002).

Panel B reveals that average *Dom* values are relatively high in Biotech, Hardware, Financial Services, and Software. This pattern suggests that more dominant-looking founders are more prevalent in industries characterized by technical complexity, high risk, and strategic decision-making, the contexts in which assertiveness and perceived authority may be particularly valuable. These are also sectors commonly associated with masculine stereotypes (e.g., Leslie et al., 2015).

In contrast, Panel C shows that the *YoAt* factor is particularly low in Hardware and Biotech, suggesting that founders in these sectors are generally perceived as older or less conventionally attractive, possibly reflecting the technical expertise and experience these industries require. The sector with the highest *YoAt* average is Consumer Products and Services, in which youthfulness and attractiveness may be more culturally or commercially valued, especially in consumer-facing ventures (Hamermesh and Biddle, 1994, Stinebrickner et al., 2019). Together, these observations highlight that face factors vary systematically across industries and may reflect sectoral norms and expectations.

Table 5 reports the estimates of the tests of how the face factors relate to the likelihood of receiving venture capital financing across industries. The results indicate that face-based impressions matter more in some sectors than they do in others. Moreover, these findings suggest that, when a facial trait is widely present within a sector, it becomes less informative for VCs as a differentiating signal. In sectors in which most founders already appear highly trustworthy, dominant, or youthful and attractive, marginal differences in corresponding face impressions may carry less weight in investment decisions.

Indeed, although the Healthcare industry exhibits the highest average *Trust* in Figure 3, columns (5) and (6) of Table 5 show that *Trust* has no significant effect on the probability of VC financing in this sector, whereas the *YoAt* factor is significantly and positively associated

with VC financing. Founders who appear younger and more attractive are more likely to secure funding in this sector, in which *Trust* is already high and thus likely less differentiating. Overall, *Trust* appears to be a strong and significant predictor of VC financing in most sectors except Healthcare, Biotech, and Hardware, while *YoAt* is significant only in Healthcare (and not in Consumer Products and Services, where its average is highest). *Dom*, a factor more prevalent in Biotech and Hardware, is insignificant in these sectors but is significantly associated with VC financing in Financial Services and Healthcare. This further supports the idea that when a trait is widely present within a sector, it may lose its value as a differentiating signal. In such settings, a more dominant appearance does not necessarily translate into a financing advantage relative to peers in the same sector.

Overall, these findings highlight that the influence of face factors on VC financing is industry-specific. *Trust* appears to be a broadly influential trait, especially in the sectors in which perceived reliability is critical. In contrast, the effects of *Dom* and *YoAt* are more nuanced, with their significance shaped by sector-specific norms. We also observe that the influence of face factors tends to diminish in contexts in which they are already widespread. These results suggest that face-based impressions are not uniformly informative and reinforce the importance of considering industry norms and expectations when interpreting the role of face factors in VC financing.

5 Post-Investment Outcomes

Initial financing captures the first step in the venture funding process. Examining post-investment outcomes offers critical insights into the longer-term implications of investor decisions. To develop a more comprehensive understanding of the role of face factors in startup success and growth trajectories, this section analyzes how face factors relate to

subsequent outcomes such as the amounts raised, the probability of securing additional financing, the attainment of high valuation benchmarks (e.g., unicorn status), and eventual exit events. This multifaceted approach enables an assessment of whether the influence of face factors persists beyond early-stage funding decisions, and whether face-based impressions carry informational value regarding long-term startup performance.

5.1 VC-Backed Startups

This subsection focuses on startup outcomes conditional on having secured initial VC financing. These results offer valuable insights into how face factors influence startup funding and performance at the intensive margin, after startups succeed in obtaining initial VC funding. We examine how much capital these startups raise, their likelihood of securing follow-on financing, and the attainment of high-valuation milestones such as unicorn status. This approach helps assess whether face-based impressions extend beyond the initial investment decision.

5.1.1 Amount Raised

We first examine how face factors relate to the amounts raised by VC-backed startups. We analyze both the first round amount and the total amount of equity raised by firms that obtained VC financing. Studying the size of the investments offers a more nuanced perspective on investor confidence, complementing our earlier analysis of funding outcomes to assess whether face factors also shape the magnitude of financial commitments. Table 6 shows that, conditional on receiving VC financing, *Dom* emerges as the most robust indicator of the amount raised both in the first round (columns (1) to (3)) and in total (columns (4) to (6)). We conjecture that founders perceived as more dominant either inspire greater investor confidence regarding future success, or more effectively negotiate during fundraising. In

contrast, neither *Trust* nor *Yoat* exhibit a significant relation with either outcome, indicating that perceived trustworthiness and youth/attractiveness may play a more limited role once initial contact is established.

5.1.2 Second Round

As interactions between VCs and founders increase over time, the influence of face-based impressions may diminish, leaving more room for objective, business-related factors to drive decision-making as the startup grows and matures. Consequently, one might expect face factors to play a less critical role in securing a second round of financing. To test this hypothesis, we examine the relation between the likelihood of securing follow-on financing and face factors. We report the results in Table 7 replicating our main specifications using second-round financing as the outcome variable, within the restricted sample of startups that received a first VC round. We find that all three face factors continue to exhibit strong positive associations with the probability of obtaining follow-on funding. This suggests that the influence of face-based impressions persists beyond initial funding. Thus, face factors may continue to shape perceptions beyond the initial round and act as persistent signals in the evaluation of founders. Such long-lasting effects might also reflect the informational value of face factors regarding startup survival and performance. Therefore, face factors may serve not only as initial heuristics but also as imperfect proxies for founder traits that influence venture outcomes.

5.1.3 Unicorn Status

We next examine the relation between face impressions and the likelihood of reaching unicorn status. Given that VCs are particularly focused on identifying "home runs" that deliver outsized returns and offset the high failure rate of early-stage investments, becoming

a unicorn represents a particularly meaningful measure of success. Fewer than 1% of startups surpass the $1 billion valuation threshold, making them a sharp lens for understanding the factors behind extraordinary entrepreneurial outcomes. We identify unicorns using Crunchbase tags, cross-checked and completed with the CB Insights' list of unicorns as of May 2025.

Table 8 presents the corresponding results and reveals a consistent and statistically significant positive association between the probability of achieving unicorn status and *YoAt*. This relation holds across multiple model specifications, even after including fixed effects in columns (2) to (3). Whereas *Trust* played a key role in initial VC funding and obtaining a follow-on round, it does not significantly predict the likelihood of reaching unicorn status once financing has been secured. As for *Dom*, there is a weakly positive effect only in the simplest specification (column (1)). However, this effect disappears once fixed effects are included in the specification (columns (2) and (3)), suggesting that dominance is not a robust predictor of the unicorn status. In contrast, *YoAT* remains significantly associated with unicorn status in all specifications, potentially reflecting not only appearance-driven biases but also underlying factors correlated with youth and attractiveness (e.g., energy, charisma, media appeal, marketability) that may continue to benefit founders as their ventures scale.

Overall, these findings suggest that although all three face factors shape investor perception and early-stage funding decisions, not all factors might translate into superior long-term performance. Whereas trustworthiness and dominance help secure financing, only youthfulness/attractiveness remains predictive of unicorn status. This suggests that certain founder attributes may offer more enduring advantages beyond the initial pitch.

5.2 Exit Outcomes

Having examined post-investment trajectories among VC-backed startups, we now extend our analyses to exploring successful exit outcomes across the entire startup population. This analysis captures firm-level outcomes regardless of financing path, allowing us to assess whether face factors are predictive of long-term success beyond the VC-backed firms. In Table 9, we define a successful exit as either an IPO or an M&A. Columns (1) to (3) present estimates for the overall probability of exit. We find that the likelihood of a successful exist is positively associated with both *Trust* and *Dom*. In our most comprehensive specification, a one standard deviation increase in *Trust* corresponds to a 3.9 percent increase in the probability of success, whereas a one standard deviation increase in *Dom* is associated with a 2.8 percent increase in the probability of success. In contrast to the unicorn analyses, limited to VC-backed firms, *YoAt* does not exhibit a significant relation with exit probability in the full sample. This suggests that the advantages associated with youthful and attractive appearance may be more relevant for exceptional, high-visibility outcomes such as achieving unicorn status, the domains in which investor attention, media presence, and public perception play a larger role.

Columns (4) to (9) of Table 9 provide a breakdown of the results by exit type – IPO versus M&A. The positive associations observed for *Trust* and *Dom* are primarily driven by acquisitions. Whereas both factors significantly increase the likelihood of being acquired, all face factor coefficients turn negative when predicting IPOs. Among them, only *Trust* is consistently significantly associated with the probability of going public. Although *YoAt* shows a negative effect in columns (4) and (5), it diminishes and becomes statistically insignificant once industry fixed effects are included in the specification.

Overall, these findings highlight that face factors, especially *Trust* and *Dom*, play a

meaningful role in shaping acquisition outcomes, whereas their influence on IPOs appears more limited and nuanced.[24]

5.2.1 Exits - Counterfactual Analysis

In this subsection, we analyze the relation between exit outcomes and face factors within the subsample of non-VC-backed firms. Focusing on a counterfactual group not influenced by VC selection or treatment allows us to examine whether face factors can predict venture outcomes regardless of VC involvement. Whereas not perfect, this comparison provides a useful lens for evaluating the robustness of the face-based predictors. Such an analysis also helps us understand whether VCs may be overlooking promising opportunities by overemphasizing specific factors, such as *Trust*, and undervaluing others that better predict success.

Table 10 presenting the analyses of the performance for non-VC-backed firms, reveals that this is not the case. *Trust* remains a strong and significant predictor of acquisition success in this subsample. However, the effect of *Dom* appears weaker compared to the full sample. The persistence of the positive association between *Trust* and M&A exits within the non-VC-backed subsample suggests that *Trust* is a robust and consistent predictor of acquisition outcome, regardless of VC involvement.

Overall, our results indicate that all analyzed face factors on which VC investors appear to rely when making financing decisions are significantly related to startup outcomes, albeit in distinct ways. *Trust* emerges as the most influential trait, with its positive effect primarily concentrated in acquisition outcomes, a relation further confirmed within the non-VC-backed subsample. *Dom* also contributes to the prediction of acquisition outcomes and stands out especially strongly in predicting the amount of capital raised. At the same time, *YoAt*

[24]This evidence is consistent with Jang and Kaplan (2025), who find that team characteristics help predict smaller VC rounds but have limited explanatory power for large-scale funding or long-term company success.

remains a robust predictor of achieving unicorn status.

Taken together, these findings suggest that VCs may not be making irrational decisions by relying on facial cues. In fact, face factors are significant predictors of both more common types of exits, such as acquisitions, and rarer outcomes, like unicorn status. Therefore, facial cues might indeed capture subtle signals that align with entrepreneurial success. We do not claim that such impressions necessarily reflect founder intrinsic ability; their effects may instead stem from societal biases that become self-fulfilling, as investor perceptions shape access to capital and subsequent opportunities. These results should thus be interpreted with caution, especially regarding the broader implications of relying on facial impressions in investment decision-making.

6 Conclusion

This study provides novel evidence that face-based impression factors significantly predict venture capital financing decisions. Perceived traits such as trustworthiness, dominance, and attractiveness/youthfulness emerge as strong predictors of funding outcomes, with effects that are both statistically robust and economically meaningful. These effects are highly context-dependent, varying with founder gender, team composition, and industry sector.

Beyond the initial investment decision, face factors predict not only the amount of capital raised but also the likelihood of securing follow-on financing. Whereas all three face factors are positively associated with the probability of obtaining a second round of funding, *Dom* uniquely predicts the scale of capital raised. Additionally, we show that face factors relate to longer-term performance: perceived youth/attractiveness is positively associated with achieving unicorn status, whereas *Trust* and *Dom* strongly predict acquisition outcomes.

These findings suggest that even experienced and sophisticated investors may, consciously

or unconsciously, rely on facial cues when evaluating founders. Rather than reflecting pure irrationality, these intuitive judgments may serve as imperfect but informative signals of founder qualities relevant to venture success.

References

Alpeyev, P. (2020). Softbank's Masayoshi Son and Alibaba's Jack Ma part ways. *Bloomberg*. Published on June 25, 2020.

Amornsiripanitch, N., Gompers, P., Hu, G., Levinson, W., and Mukharlyamov, V. (2022). Failing just fine: Assessing careers of venture capital-backed entrepreneurs via a non-wage measure. *Working Paper*.

Bernstein, S., Korteweg, A., and Laws, K. (2017). Attracting early-stage investors: Evidence from a randomized field experiment. *The Journal of Finance*, 72(2):509–538.

Blankespoor, E., Hendricks, B. E., and Miller, G. S. (2017). Perceptions and price: Evidence from ceo presentations at ipo roadshows. *Journal of Accounting Research*, 55(2):275–327.

Cao, Y., Guan, F., Li, Z., and Yang, Y. G. (2020). Analysts' beauty and performance. *Management Science*, 66(9):4315–4335.

Cohen, S., Fehder, D. C., Hochberg, Y. V., and Murray, F. (2019). The design of startup accelerators. *Research Policy*, 48(7):1781–1797.

Dalle, J.-M., den Besten, M., and Menon, C. (2017). Using crunchbase for economic and managerial research. *Working Paper*.

Duan, Y., Hsieh, T.-S., Wang, R. R., and Wang, Z. (2020). Entrepreneurs' facial trustworthiness, gender, and crowdfunding success. *Journal of Corporate Finance*, 64:101693.

Duarte, J., Siegel, S., and Young, L. (2012). Trust and credit: The role of appearance in peer-to-peer lending. *The Review of Financial Studies*, 25(8):2455–2484.

Duncan, J. and Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological review*, 96(3):433.

Ewens, M. and Farre-Mensa, J. (2020). The deregulation of the private equity markets and the decline in ipos. *The Review of Financial Studies*, 33(12):5463–5509.

Ewens, M. and Townsend, R. R. (2020). Are early stage investors biased against women? *Journal of Financial Economics*, 135(3):653–677.

Gheorghiu, A. I., Callan, M. J., and Skylark, W. J. (2017). Facial appearance affects science communication. *Proceedings of the National Academy of Sciences*, 114(23):5970–5975.

Goldin, C. and Rouse, C. (2000). Orchestrating impartiality: The impact of" blind" auditions on female musicians. *American economic review*, 90(4):715–741.

Gompers, P. A., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, 135(1):169–190.

Gompers, P. A., Mukharlyamov, V., and Xuan, Y. (2016). The cost of friendship. *Journal of Financial Economics*, 119(3):626–644.

Gonzalez-Uribe, J., Klingler-Vidra, R., Wang, S., and Yin, X. (2023). The broader impact of venture capital on innovation: Reducing entrepreneurial capability constraints through due diligence. *Working Paper*.

Gornall, W. and Strebulaev, I. A. (2021). The economic impact of venture capital: Evidence from public companies. *Available at SSRN 2681841*.

Graham, J. R., Harvey, C. R., and Puri, M. (2017). A corporate beauty contest. *Management Science*, 63(9):3044–3056.

Guenzel, M., Kogan, S., Niessner, M., and Shue, K. (2025). Ai personality extraction from faces: Labor market implications. *SSRN Electronic Journal*.

Hamermesh, D. S. and Biddle, J. E. (1994). Beauty and the labor market. *The American Economic Review*, pages 1174–1194.

He, X., Yin, Y., Zeng, H., Zhang, H., and Zhao, H. (2019). Facial structure and achievement drive: Evidence from financial analysts. *Journal of Accounting Research*, 57(4):1013–1057.

Hebert, C. (2020). Gender stereotypes and entrepreneur financing. In *10th Miami Behavioral Finance Conference*.

Hellmann, T., Schure, P., and Vo, D. H. (2021). Angels and venture capitalists: Substitutes or complements? *Journal of Financial Economics*, 141(2):454–478.

Hsieh, T. S., Kim, J.-B., Wang, R., and Wang, Z. (2020). Seeing is believing? executives' facial trustworthiness, auditor tenure, and audit fees. *Journal of Accounting and Economics*, 69(1):1–23.

Hu, A. and Ma, S. (2025). Persuading Investors: A Video-Based Study. *Journal of Finance*. Forthcoming.

Huang, X., Ivković, Z., Jiang, J. X., and Wang, I. Y. (2023). Angel investment and first impressions. *Journal of Financial Economics*, 149(2):161–178.

Jaeger, B., Todorov, A. T., Evans, A. M., and van Beest, I. (2020). Can we reduce facial biases? persistent effects of facial trustworthiness on sentencing decisions. *Journal of Experimental Social Psychology*, 90:104004.

Jang, Y. S. and Kaplan, S. N. (2025). Venture capital start-up selection. Technical report, National Bureau of Economic Research.

Jia, Y., Van Lent, L., and Zeng, Y. (2014). Masculinity, testosterone, and financial misreporting. *Journal of Accounting Research*, 52(5):1195–1246.

Kaplan, S. N., Sensoy, B. A., and Strömberg, P. (2009). Should investors bet on the jockey or the horse? Evidence from the evolution of firms from early business plans to public companies. *The Journal of Finance*, 64(1):75–115.

Kaplan, S. N. and Strömberg, P. (2000). How do venture capitalists choose investments. *Workng Paper, University of Chicago*, 121:55–93.

Kaplan, S. N. and Stromberg, P. (2004). Characteristics, contracts, and actions: Evidence from venture capitalist analyses. *The Journal of Finance*, 59(5):2177–2210.

Lerner, J., Schoar, A., Sokolinski, S., and Wilson, K. (2018). The globalization of angel investments: Evidence across countries. *Journal of Financial Economics*, 127(1):1–20.

Leslie, S.-J., Cimpian, A., Meyer, M., and Freeland, E. (2015). Expectations of brilliance underlie gender distributions across academic disciplines. *Science*, 347(6219):262–265.

Li, C., Lin, A. P., Lu, H., and Veenstra, K. (2020). Gender and beauty in the financial analyst profession: Evidence from the united states and china. *Review of Accounting Studies*, 25(4):1230–1260.

Linke, L., Saribay, S. A., and Kleisner, K. (2016). Perceived trustworthiness is associated with position in a corporate hierarchy. *Personality and Individual Differences*, 99:22–27.

Market.us (2025). Startup Accelerator Market. *Market Research Report*. Accessed on August 8, 2025.

Mobius, M. M. and Rosenblat, T. S. (2006). Why beauty matters. *American Economic Review*, 96(1):222–235.

Mordor Intelligence (2025). United States Venture Capital Market & Share Analysis - Growth Trends & Forecasts (2025 - 2030). Accessed on August 8, 2025.

Oh, D., Buck, E. A., and Todorov, A. (2019). Revealing hidden gender biases in competence impressions of faces. *Psychological science*, 30(1):65–79.

Olivola, C. Y. and Todorov, A. (2010). Elected in 100 milliseconds: Appearance-based trait inferences and voting. *Journal of nonverbal behavior*, 34:83–110.

Oosterhof, N. N. and Todorov, A. (2008). The functional basis of face evaluation. *Proceedings of the National Academy of Sciences*, 105(32):11087–11092.

Peng, L., Teoh, S. H., Wang, Y., and Yan, J. (2022). Face value: Trait impressions, performance characteristics, and market outcomes for financial analysts. *Journal of Accounting Research*, 60(2):653–705.

Puri, M. and Zarutskie, R. (2012). On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms. *The Journal of Finance*, 67(6):2247–2293.

Retterath, A. and Braun, R. (2020). Benchmarking venture capital databases. *Working Paper*.

Schiller, D., Freeman, J. B., Mitchell, J. P., Uleman, J. S., and Phelps, E. A. (2009). A neural mechanism of first impressions. *Nature Neuroscience*, 12(4):508–514.

Sirdeshmukh, D., Singh, J., and Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. *Journal of marketing*, 66(1):15–37.

Stinebrickner, R., Stinebrickner, T., and Sullivan, P. (2019). Beauty, job tasks, and wages: A new conclusion about employer taste-based discrimination. *The Review of Economics and Statistics*, 101(4):602–615.

Sutherland, C. A., Oldmeadow, J. A., Santos, I. M., Towler, J., Burt, D. M., and Young, A. W. (2013). Social inferences from faces: Ambient images generate a three-dimensional model. *Cognition*, 127(1):105–118.

Tamaseb, A. (2021). *Super founders: What data reveals about billion-Dollar startups*. PublicAffairs.

TechCrunch Events (2025). At TechCrunch all stage, Charles Hudson will tell you what investors really see. *TechCrunch*. Published on June 30, 2025.

Todorov, A. (2017). Face value: The irresistible influence of first impressions. In *Face value*. Princeton University Press.

Todorov, A., Mandisodza, A. N., Goren, A., and Hall, C. C. (2005). Inferences of competence from faces predict election outcomes. *Science*, 308(5728):1623–1626.

Vernon, R. J., Sutherland, C. A., Young, A. W., and Hartley, T. (2014). Modeling first impressions from highly variable facial images. *Proceedings of the National Academy of Sciences*, 111(32):E3353–E3361.

Wolfe, J. M. (2000). Visual attention. *Seeing*, pages 335–386.

Zebrowitz, L. A. and McDonald, S. M. (1991). The impact of litigants' baby-facedness and attractiveness on adjudications in small claims courts. *Law and Human Behavior*, 15(6):603–623.

Figure 1: Face Factors by the VC-Backing Status of the Company. This figure shows the mean of each of the three factors (Trust, YoAt, Dom) for VC-backed companies and companies without any financing.

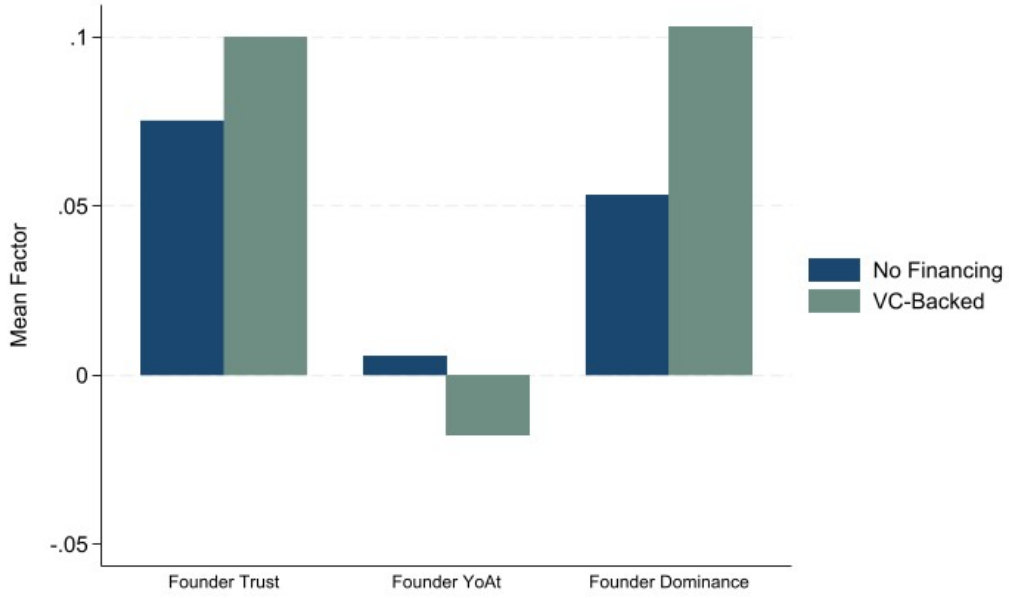


Figure 2: Face Factors by Founder Gender. This figure shows the mean of each of the three factors (Trust, YoAt, Dom) for female and male founders.

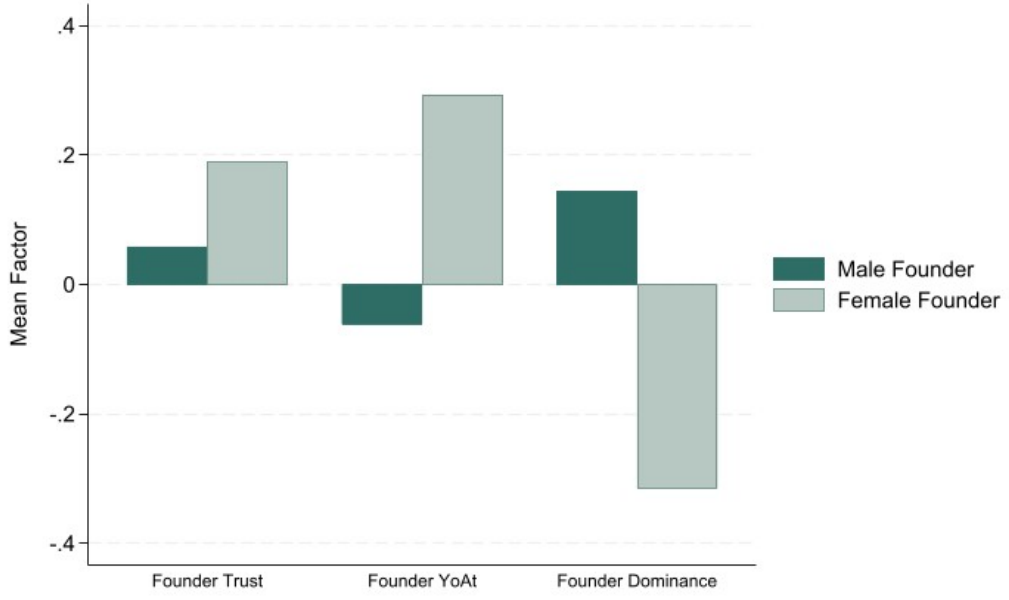
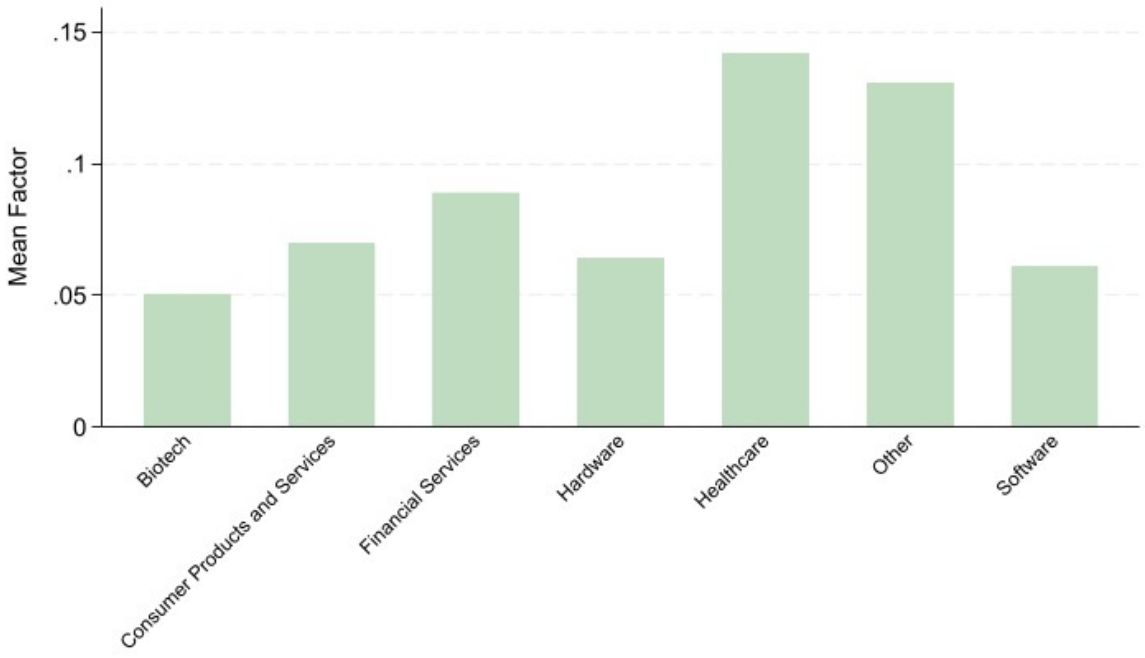


Figure 3: Face Factors by Industry. This figure shows the mean of each of the three factors (Trust, YoAt, Dom) by industry.

Panel A. Founder Trust



Panel B. Founder Dominance

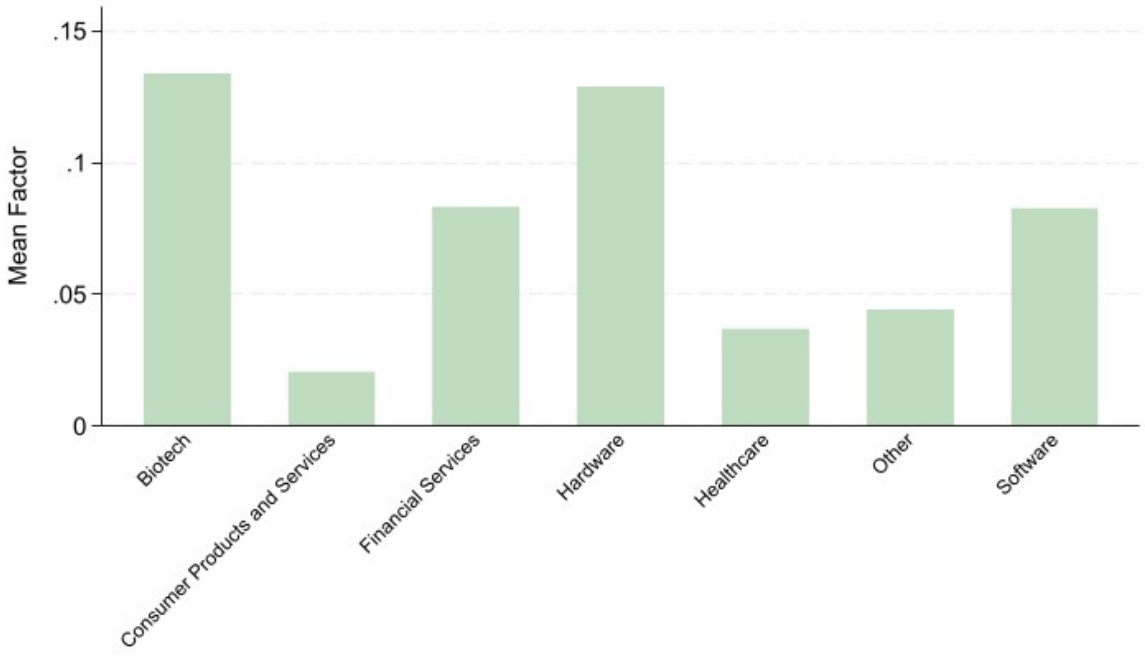


Figure 4: Face Factors by Industry - Cont'd

Panel C. Founder YoAt

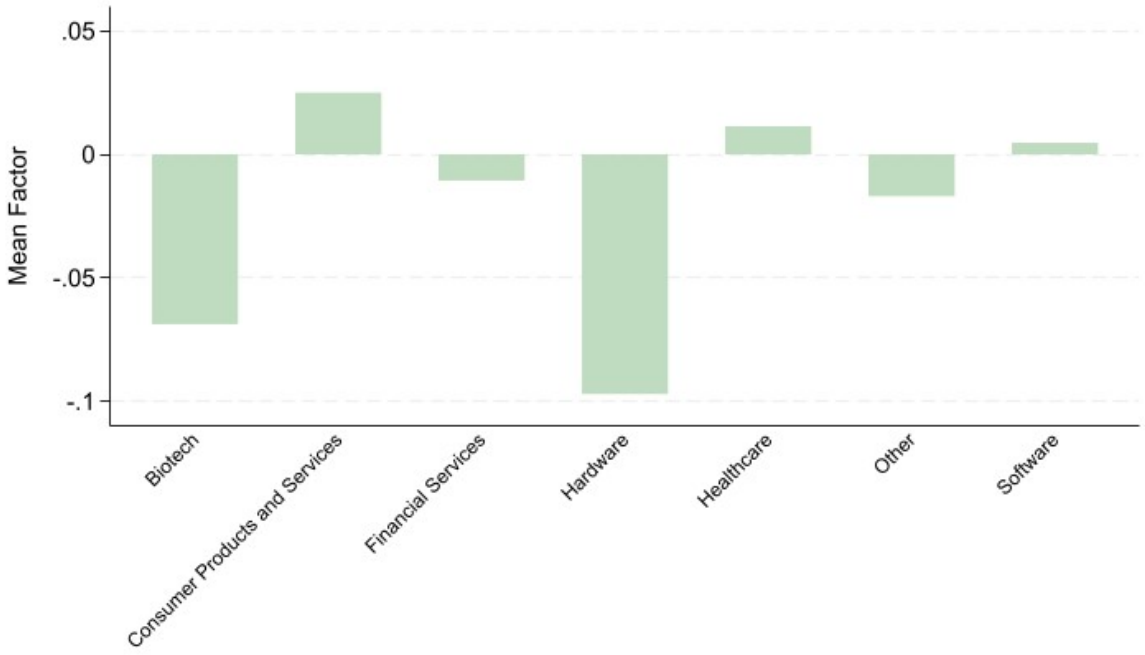


Table 1: Descriptive Statistics. This table presents the summary statistics for the main variables used in the analysis at the firm level. *Panel A* reports company characteristics, *Panel B* shows average founder characteristics at the startup team level. Statistics at the founder level are reported in Table A2. The dataset includes U.S. startups founded between 2012 and 2021, for which facial feature data is available for more than half of the founding team. At the investment level, the data include the first round of financing from the lead U.S.-based VC investor. See Appendix Table A1 for detailed variable definitions.

	N Obs	Mean	Std. Dev.	Min	Median	Max
Panel A: Company characteristics						
Face Factors						
Trust	57,460	0.08	0.45	-1.00	0.12	1.00
Yoat	57,460	0.00	0.39	-1.00	-0.00	1.00
Dom	57,460	0.06	0.39	-1.00	0.07	1.00
Firm & Team Characteristics						
Founding Year	57,460	2016	2.67	2012	2016	2021
Founding Team Size	57,460	1.46	0.82	1.00	1.00	20.00
Solo-founded	57,460	0.69	0.46	0.00	1.00	1.00
Ethnically Diverse	57,460	0.02	0.12	0.00	0.00	1.00
Female-founded	57,460	0.23	0.42	0.00	0.00	1.00
VC Financing	57,460	0.17	0.37	0.00	0.00	1.00
Location						
CA company	57,460	0.28	0.45	0.00	0.00	1.00
NY company	57,460	0.13	0.33	0.00	0.00	1.00
MA company	57,460	0.04	0.19	0.00	0.00	1.00
Exit Outcomes						
Exit	57,460	0.07	0.25	0.00	0.00	1.00
IPO	57,460	0.00	0.07	0.00	0.00	1.00
M&A	57,460	0.06	0.25	0.00	0.00	1.00
VC-Backed Companies						
Funding Year	9,496	2017.75	2.98	2012	2018	2024
Age at Financing	9,496	2.65	1.73	1.00	2.00	13.00
N. Rounds	9,496	3.10	2.21	1.00	3.00	21.00
First Round Size (M USD)	6,592	8.90	45.73	0.001	3.20	3,000
Ln(First Round Size)	6,592	1.15	1.46	-6.91	1.16	8.01
Total Equity Raised (M USD)	8,074	61.18	246.45	0.001	12	13,997
Ln(Total Equity Raised)	8,074	2.47	1.93	-6.91	2.48	9.55
Second Round	9,496	0.59	0.49	0.00	1.00	1.00
Seed Stage	9,496	0.68	0.47	0.00	1.00	1.00
Early Stage	9,496	0.21	0.41	0.00	0.00	1.00

Table 1: Descriptive Statistics - Cont'd

	N Obs	Mean	Std. Dev.	Min	Median	Max
Panel B: Founding team characteristics						
Founder Age (Years)	57,460	31.39	8.20	18.00	28.00	58.00
Education & Work Experience						
Completed by founding time						
Bachelor Degree	28,077	0.90	0.29	0.00	1.00	1.00
Master Degree	28,077	0.28	0.44	0.00	0.00	1.00
Ph.D. Degree	28,077	0.11	0.30	0.00	0.00	1.00
MBA Degree	28,077	0.14	0.34	0.00	0.00	1.00
STEM Degree	28,077	0.35	0.48	0.00	0.00	1.00
Elite School Degree	28,077	0.17	0.36	0.00	0.00	1.00
Missing founder education	57,460	0.51	0.50	0.00	1.00	1.00
Work experience						
Work Experience (Years)	57,460	3.80	6.22	0.00	0.50	50
N. of Prev. Jobs	57,460	1.01	1.60	0.00	0.17	10
Founder Experience	57,460	0.31	0.44	0.00	0.00	1.00
CEO Experience	57,460	0.14	0.32	0.00	0.00	1.00
C-suite Experience	57,460	0.06	0.22	0.00	0.00	1.00
Chief Experience	57,460	0.14	0.32	0.00	0.00	1.00
Investor Experience	57,460	0.03	0.14	0.00	0.00	1.00
Top Employer Experience	57,460	0.02	0.13	0.00	0.00	1.00

Table 2: Face Factors and the Likelihood of VC Financing. This table reports linear regression estimates of the probability of receiving venture capital financing based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. All the columns contain basic firm-level controls and detailed controls for founder characteristics (averaged at the firm level). Columns (2) and (3) progressively include founding year x state fixed effects and industry group fixed effects. Founder experience variables capture work experience accumulated prior to the company's founding; education variables reflect degrees completed before founding the company. See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)		
	(1)	(2)	(3)
Trust	0.020***	0.022***	0.026***
	(0.003)	(0.003)	(0.003)
YoAt	0.012***	0.009**	0.009**
	(0.004)	(0.004)	(0.004)
Dom	0.014***	0.012***	0.011***
	(0.004)	(0.004)	(0.004)
Female-founded	-0.029***	-0.031***	-0.016***
	(0.004)	(0.004)	(0.004)
Founding Team Size	0.157***	0.151***	0.132***
	(0.003)	(0.003)	(0.003)
Founder Age	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
Founder Experience	0.007*	0.003	0.005
	(0.004)	(0.004)	(0.004)
CEO Experience	0.035***	0.034***	0.026***
	(0.005)	(0.005)	(0.005)
C-suite Experience	0.066***	0.059***	0.049***
	(0.008)	(0.008)	(0.008)
Chief Experience	0.029***	0.026***	0.027***
	(0.005)	(0.005)	(0.005)
Investor Experience	0.167***	0.156***	0.154***
	(0.014)	(0.013)	(0.013)
Top Employer Experience	0.136***	0.115***	0.114***
	(0.015)	(0.014)	(0.014)
Work Experience (Years)	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)
Elite School Degree	0.146***	0.127***	0.118***
	(0.007)	(0.007)	(0.007)
Master Degree	0.005	0.004	-0.009
	(0.006)	(0.006)	(0.005)
PhD Degree	0.099***	0.092***	0.046***
	(0.009)	(0.009)	(0.009)
MBA Degree	0.013**	0.013**	0.009
	(0.006)	(0.006)	(0.006)
STEM Degree	0.059***	0.055***	0.030***
	(0.004)	(0.004)	(0.004)
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	57,460	57,454	57,454
R-squared	0.179	0.200	0.251

Table 3: Face Factors and the Likelihood of VC Financing - Variation by Founders' Gender. This table replicates the results from Table 2 restricting the initial sample to male-only companies (columns (1) to (3)), mixed-gender founding teams (columns (4) to (6)), and female-only companies (columns (7) to (9)). It reports linear regression estimates of the probability of receiving venture capital financing based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. All the columns contain basic firm-level controls and detailed controls for founder characteristics (averaged at the firm level). Columns (2), (5), (8) additionally include founding year x state fixed effects, and columns (3), (6), (9) further add industry group fixed effects. See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)								
	Male-only			Mixed-Gender			Female-only		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trust	0.020***	0.021***	0.026***	0.064***	0.072***	0.076***	-0.001	0.002	0.006
	(0.003)	(0.003)	(0.003)	(0.019)	(0.020)	(0.020)	(0.006)	(0.006)	(0.006)
YoAt	0.007	0.004	0.004	0.049*	0.053**	0.056**	0.016**	0.012	0.010
	(0.005)	(0.005)	(0.005)	(0.025)	(0.027)	(0.026)	(0.008)	(0.008)	(0.008)
Dom	0.015***	0.013***	0.014***	0.068**	0.071**	0.073***	0.014	0.011	0.008
	(0.005)	(0.005)	(0.005)	(0.028)	(0.029)	(0.028)	(0.009)	(0.010)	(0.009)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year x State	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry Group	No	No	Yes	No	No	Yes	No	No	Yes
Observations	44,435	44,425	44,425	4,493	4,416	4,416	8,531	8,462	8,462
R-squared	0.179	0.202	0.251	0.148	0.227	0.302	0.074	0.118	0.176

Table 4: Face Factors and the Likelihood of VC Financing - Variation by Founding Team Structure. This table replicates the results from Table 2 restricting the initial sample to solo-founded companies (columns (1) to (3)) and to multi-founders companies (columns (4) to (6)). It reports linear regression estimates of the probability of receiving venture capital financing based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. All the columns contain basic firm-level controls and detailed controls for founder characteristics (averaged at the firm level). Columns (2) and (5) additionally include founding year x state fixed effects, and columns (3) and (6) further add industry group fixed effects. Robust standard errors are reported in parentheses. See Appendix Table A1 for detailed variable definitions. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)					
	Solo Founders			Multi-Founder Teams		
	(1)	(2)	(3)	(4)	(5)	(6)
Trust	0.004	0.005*	0.008***	0.066***	0.071***	0.076***
	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.010)
YoAt	0.004	0.002	0.002	0.032**	0.030**	0.022*
	(0.004)	(0.004)	(0.004)	(0.014)	(0.014)	(0.013)
Dom	0.005	0.003	0.004	0.077***	0.079***	0.065***
	(0.004)	(0.004)	(0.004)	(0.014)	(0.014)	(0.013)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year x State	No	Yes	Yes	No	Yes	Yes
Industry Group	No	No	Yes	No	No	Yes
Observations	39,613	39,605	39,605	17,847	17,803	17,803
R-squared	0.026	0.046	0.100	0.096	0.148	0.224

Table 5: Face Factors and the Likelihood of VC Financing - Variation by Industry. This table replicates the results from Table 2 by splitting the sample by broad industry sectors (see Table A7 for the classification of Crunchbase industry groups into these broad categories). It reports linear regression estimates of the probability of receiving venture capital financing based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. All the columns contain basic firm-level controls, detailed controls for founder characteristics (averaged at the firm level), and founding year x state fixed effects. Even columns additionally include industry group fixed effects (significantly more granular than the industry classifications used for the sample splits). Robust standard errors are reported in parentheses. See Appendix Table A1 for detailed variable definitions. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)							
	Software		Financial Services		Healthcare		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust	0.035***	0.037***	0.026***	0.032***	0.014	0.016	0.016**	0.020***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.010)	(0.010)	(0.007)	(0.007)
YoAt	0.003	0.001	0.005	0.002	0.036***	0.034**	0.006	0.015
	(0.008)	(0.008)	(0.011)	(0.011)	(0.014)	(0.014)	(0.010)	(0.010)
Dom	0.005	0.007	0.031***	0.032***	0.026*	0.029**	-0.002	-0.001
	(0.008)	(0.008)	(0.011)	(0.011)	(0.014)	(0.014)	(0.010)	(0.010)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year x State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Group	No	Yes	No	Yes	No	Yes	No	Yes
Observations	20,324	20,324	8,538	8,538	6,825	6,825	4,677	4,677
R-squared	0.219	0.257	0.212	0.259	0.228	0.254	0.142	0.183

	Consumer Prod./Serv.		Biotech		Hardware	
	(9)	(10)	(11)	(12)	(13)	(14)
Trust	0.012**	0.013***	0.036	0.032	0.019	0.018
	(0.005)	(0.005)	(0.031)	(0.031)	(0.020)	(0.018)
YoAt	0.005	0.008	0.054	0.066	0.018	0.010
	(0.006)	(0.006)	(0.043)	(0.042)	(0.027)	(0.027)
Dom	-0.003	0.000	0.049	0.041	0.020	0.017
	(0.007)	(0.007)	(0.042)	(0.041)	(0.026)	(0.025)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year x State	Yes	Yes	Yes	Yes	Yes	Yes
Industry Group	No	Yes	No	Yes	No	Yes
Observations	13,199	13,199	1,723	1,723	1,682	1,682
R^2	0.146	0.182	0.290	0.369	0.284	0.332

Table 6: Face Factors and Financing Amount. This table reports linear regression estimates of the amounts raised in the first round of VC financing and in total, based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. Columns (1) to (3) present the results where the dependent variable is the logarithm of the amount raised in the first round. Columns (4) to (6) display the results where the dependent variable is the logarithm of the total equity raised. All specifications control for basic firm-level characteristics, including the number of investors involved in the first round, and detailed founder characteristics (averaged at the firm level). They progressively incorporate funding round year fixed effects, founding year x state fixed effects, and industry group fixed effects. See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Ln(First Round Size)			Ln(Total Equity Raised)		
	(1)	(2)	(3)	(4)	(5)	(6)
Trust	-0.049	-0.065	-0.028	-0.004	0.022	0.035
	(0.047)	(0.042)	(0.041)	(0.055)	(0.055)	(0.054)
YoAt	-0.100	-0.082	-0.040	0.121	0.065	0.114
	(0.066)	(0.060)	(0.058)	(0.077)	(0.077)	(0.074)
Dom	0.108	0.147**	0.151**	0.299***	0.292***	0.275***
	(0.067)	(0.062)	(0.060)	(0.078)	(0.080)	(0.077)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes
Funding Round Year	No	Yes	Yes	No	Yes	Yes
Founding Year x State	No	Yes	Yes	No	Yes	Yes
Industry Group	No	No	Yes	No	No	Yes
Observations	6,592	6,522	6,522	8,074	7,998	7,998
R-squared	0.130	0.344	0.398	0.108	0.185	0.262

Table 7: Face Factors and Second Round of Financing. This table reports linear regression estimates of the likelihood of obtaining a second round of VC financing based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. All the columns contain basic firm-level controls, including the logarithm of the amount raised in the first round, and detailed controls for founder characteristics (averaged at the firm level). Column (2) includes funding round year and founding year x state fixed effects, and column (3) further includes industry group fixed effects. See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(Second Round)		
	(1)	(2)	(3)
Trust	0.033**	0.041***	0.034**
	(0.016)	(0.015)	(0.015)
YoAt	0.074***	0.060***	0.057***
	(0.022)	(0.022)	(0.022)
Dom	0.069***	0.053**	0.052**
	(0.023)	(0.023)	(0.023)
Basic controls	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes
Funding Round Year	No	Yes	Yes
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	6,592	6,522	6,522
R-squared	0.031	0.187	0.214

Table 8: Face Factors and Unicorn Status. This table reports linear regression estimates of the likelihood of reaching unicorn status based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. All the columns contain basic firm-level controls and detailed controls for founder characteristics (averaged at the firm level). Column (2) includes funding round year and founding year x state fixed effects, and column (3) further includes industry group fixed effects. See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(Unicorn)		
	(1)	(2)	(3)
Trust	0.002	0.003	0.002
	(0.004)	(0.005)	(0.005)
YoAt	0.016***	0.015**	0.014**
	(0.006)	(0.006)	(0.006)
Dom	0.010*	0.009	0.009
	(0.006)	(0.006)	(0.006)
Basic controls	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes
Funding Round Year	No	Yes	Yes
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	9,496	9,425	9,425
R-squared	0.022	0.048	0.062

Table 9: Face Factors and Exit Outcomes. This table reports linear regression estimates of successful exit likelihood based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. Columns (1) to (3) present the results where the dependent variable is a dummy equal to one if a firm successfully exited via IPO or M&A. Columns (4) to (6) display the results where the dependent variable equals one if a firm went public, and columns (7) to (9) when it equals one if a firm exited via an M&A. All the columns contain basic firm-level controls, including whether the firm is VC-backed, and detailed controls for founder characteristics (averaged at the firm level). They progressively incorporate founding year x state fixed effects, and industry group fixed effects. See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(All Exit)			P(IPO)			P(M&A)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trust	0.003	0.005**	0.006***	-0.002***	-0.002***	-0.001**	0.005**	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
YoAt	0.000	0.003	0.002	-0.002**	-0.001*	-0.001	0.002	0.005	0.003
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Dom	0.007**	0.006*	0.005*	-0.000	-0.000	-0.000	0.007**	0.006**	0.006*
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year x State	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry Group	No	No	Yes	No	No	Yes	No	No	Yes
Observations	57,460	57,454	57,454	57,460	57,454	57,454	57,460	57,454	57,454
R-squared	0.075	0.097	0.104	0.022	0.034	0.070	0.061	0.082	0.090

Table 10: Face Factors and Exit Outcomes - Non-VC-Backed Firms. This table replicates the results of Table 9 for the sample of non-VC-backed firms. It reports linear regression estimates of successful exit likelihood based on the founding team's average face factors (Trust, YoAt, and Dom) computed at the firm level. Columns (1) to (3) present the results where the dependent variable is a dummy equal to one if a firm successfully exited via IPO or M&A. Columns (4) to (6) display the results where the dependent variable equals one if a firm went public, and columns (7) to (9) when it equals one if a firm exited via an M&A. All the columns contain basic firm-level controls, and detailed controls for founder characteristics (averaged at the firm level). They progressively incorporate founding year x state fixed effects, and industry group fixed effects. See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(All Exit)			P(IPO)			P(M&A)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trust	0.003*	0.004**	0.005***	-0.001**	-0.001*	-0.000	0.004**	0.005**	0.006***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
YoAt	-0.002	-0.000	-0.001	-0.000	-0.000	-0.000	-0.002	-0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Dom	0.005*	0.004	0.004	-0.001	-0.001	-0.001	0.005*	0.005*	0.004
	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year x State	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry Group	No	No	Yes	No	No	Yes	No	No	Yes
Observations	47,964	47,959	47,959	47,964	47,959	47,959	47,964	47,959	47,959
R-squared	0.011	0.026	0.034	0.001	0.007	0.010	0.011	0.026	0.034

Appendix

Table A1: Variables Definition. The table describes the main variables used in the analysis.

Variable	Definition
Main Dependent Variables	
VC Financing	Dummy variable equal to one if the startup received VC financing.
Unicorn	Dummy variable equal to one if the startup is defined as a Unicorn by Crunchbase or CB Insights.
Second Round	Dummy variable equal to one if the startup has received a second round of VC financing (conditional on having VC financing).
Ln(First Round Size)	Natural logarithm of the amount raised in the first round of VC financing.
Ln(Total Equity Raised)	Natural logarithm of the total equity amount raised by the startup across all financing rounds.
Exit	Dummy variable equal to one if the startup successfully exited via an IPO or an M&A.
IPO	Dummy variable equal to one if the startup exited via an IPO.
M&A	Dummy variable equal to one if the startup exited via an M&A.
Face Factors	
Trust	Average trustworthiness score of a team. See Section 2.2 for details of the variable construction.
YoAt	Average youthfulness score of a team. See Section 2.2 for details of the variable construction.
Dom	Average dominance score of a team. See Section 2.2 for details of the variable construction.
Founder-Level Control Variables	
Founder Age (Years)	Mean age of team founders at the founding year of the startup. For founders with unavailable birth date, we estimated their birth year based on education variables (e.g., bachelor start year - 18) or inferred it from the earliest work year assuming they start working at age 25.
Bachelor Degree	Team level average of individual indicators equal to one if the founder has completed a bachelor's degree by the startup founding year.

Variable	Definition
Master Degree	Team level average of individual indicators equal to one if the founder completed a Master's degree by the startup founding year.
PhD Degree	Team level average of individual indicators equal to one if the founder completed a Ph.D. degree by the startup founding year.
MBA Degree	Team level average of individual indicators equal to one if the founder completed an MBA degree by the startup founding year.
STEM Degree	Team level average of individual indicators equal to one if the founder has completed a STEM degree by the startup founding year.
Elite School Degree	Team level average of individual indicators equal to one if the founder has completed an Elite School degree by the startup founding year. Elite Institutions are defined following Gompers et al. (2016) and Amornsiripanitch et al. (2022).
Work Experience (Years)	Average number of years of work experience across all founders, based on earliest available work year per founder.
Founder Experience	Team level average of individual indicators equal to one if the founder had a previous founding experience by the startup founding year.
CEO Experience	Team level average of individual indicators equal to one if the founder had a CEO experience by the startup founding year.
C-suite Experience	Team level average of individual indicators equal to one if the founder had C-suite experience by the startup founding year.
Chief Experience	Team level average of individual indicators equal to one if the founder had a "Chief"-titled position experience by the startup founding year.
Investor Experience	Team level average of individual indicators equal to one if the founder had an investor experience by the startup founding year.
N. of Prev. Jobs	The number of jobs listed in founder's Crunchbase profile by the startup founding year.
Top Employer Experience	Team level average of individual indicators equal to one if the founder previously worked at a top-20 company listed in the *Super Founders* book (e.g., Google, Microsoft, Meta).

Firm-Level Control Variables and Fixed Effects

Founding Year	Year the startup was founded.
Founding Team Size	Number of founders associated with the startup according to Crunchbase.
Solo-founded	Dummy variable equal to one if the startup has only one founder.
Ethnically Diverse	Dummy variable equal to one if the startup has non-white founders, as identified by Crunchbase.
Female-founded	Dummy variable equal to one if the startup has a female founder.

Variable	Definition
Mixed-gender	Dummy variable equal to one if the startup founding team includes both male and female founders.
Female-only	Dummy variable equal to one if the startup has only female founders.
CA company	Dummy variable equal to one if the startup is located in the state of California.
NY company	Dummy variable equal to one if the startup is located in the state of New York.
MA company	Dummy variable equal to one if the startup is located in the state of Massachusetts.
Funding Year	Year the startup received the analyzed round of VC funding.
Age at Financing	The difference between the firm's founding year and the year of the first VC round plus one.
N. Rounds	The number of VC rounds recorded in Crunchbase (for VC-backed startups).
Seed/Early Stage	Dummy variable equal to one if the first VC round is classified as "seed" or "early stage" financing.
Industry Group	Industry classification of the startup according to Crunchbase classification (see Table A5).

Table A2: Descriptive Statistics - Founder-Firm Level. This table presents the summary statistics for the main variables used in the analysis at the founder-firm level. The dataset includes U.S. firms founded between 2012 and 2021, with at least half of the team whose facial features are available. At the investment level, the data includes the first round of financing from the lead VC investor. See Appendix Table A1 for detailed variable definitions.

	N Obs	Mean	Std. Dev.	Min	Median	Max
Face Factors						
Trust	80,198	0.08	0.49	-1.00	0.14	1.00
Yoat	80,198	0.00	0.42	-1.00	-0.01	1.00
Dom	80,198	0.07	0.41	-1.00	0.08	1.00
Demographics						
Founder Age (Years)	80,198	31.27	8.58	18.00	27.00	58.00
Female	79,504	0.17	0.38	0.00	0.00	1.00
Education						
Completed by founding time						
Bachelor Degree	48,160	0.62	0.48	0.00	1.00	1.00
Master Degree	48,160	0.20	0.40	0.00	0.00	1.00
Ph.D. Degree	48,160	0.08	0.27	0.00	0.00	1.00
MBA Degree	48,160	0.10	0.30	0.00	0.00	1.00
STEM Degree	48,160	0.27	0.45	0.00	0.00	1.00
Elite School Degree	48,160	0.12	0.33	0.00	0.00	1.00
Missing founder education	80,198	0.40	0.49	0.00	0.00	1.00
Work experience						
Work Experience (Years)	80,198	3.85	6.65	0.00	0.00	50.00
N. of Prev. Jobs	80,198	1.05	1.79	0.00	0.00	10.00
Founder Experience	80,198	0.32	0.46	0.00	0.00	1.00
CEO Experience	80,198	0.14	0.34	0.00	0.00	1.00
C-suite Experience	80,198	0.07	0.26	0.00	0.00	1.00
Chief Experience	80,198	0.15	0.35	0.00	0.00	1.00
Investor Experience	80,198	0.03	0.17	0.00	0.00	1.00
Top Employer Experience	80,198	0.03	0.16	0.00	0.00	1.00

Table A3: Sample filtering - Attrition. This table reports, for each step, the number of units and the percentage relative to the initial dataset. *Distinct Founder–Company Pairs* are unique founder–startup pairs; *Distinct Companies*, *Distinct Investors*, and *Distinct Rounds* refer to unique startups, investors, and unique first financing rounds, respectively.

	N	%
Panel A. Overall Dataset		
Distinct Founder-Company Pairs	950,963	100.00
Distinct Companies	656,219	100.00
Distinct Investors	123,038	100.00
Distinct Rounds	361,659	100.00
Panel B. Initial Screening		
Drop inconsistent round reports		
Distinct Founder-Company Pairs	879,612	92.50
Distinct Companies	612,083	93.27
Distinct Investors	121,725	98.93
Distinct Rounds	357,268	98.79
First rounds & lead investors only; if VC-backed: VC rounds only		
Distinct Founder-Company Pairs	778,627	81.88
Distinct Companies	559,449	85.25
Distinct Investors	25,840	21.00
Distinct Rounds	114,679	31.71
Panel C. Sample Filters		
US companies & US investors only		
Distinct Founder-Company Pairs	350,305	36.84
Distinct Companies	256,171	39.03
Distinct Investors	9,420	7.66
Distinct Rounds	43,259	11.96
Drop inconsistent startup age or exit date, drop duplicate obs		
Distinct Founder-Company Pairs	348,332	36.62
Distinct Companies	255,513	38.94
Distinct Investors	9,161	7.44
Distinct Rounds	42,513	11.75
Keep founded 2012–2021		
Distinct Founder-Company Pairs	153,895	16.18
Distinct Companies	103,711	15.80
Distinct Investors	6,261	5.09
Distinct Rounds	24,601	6.80
Either VC only or zero financing		
Distinct Founder-Company Pairs	129,901	13.66
Distinct Companies	90,936	13.86
Distinct Investors	2,856	2.32
Distinct Rounds	11,826	3.27
Face factors available for most of the team		
Distinct Founder-Company Pairs	83,891	8.82
Distinct Companies	59,083	9.00
Distinct Investors	2,512	2.04
Distinct Rounds	9,598	2.65
Drop if missing founder age		
Distinct Founder-Company Pairs	80,198	8.43
Distinct Companies	57,460	8.76
Distinct Investors	2,498	2.03
Distinct Rounds	9,496	2.63

Table A4: Descriptive statistics for Face Sample versus Full Sample. This table presents the results of a t-test comparing descriptive statistics between the sample with face factors (Face Sample) and the sample that does not require face factors (Full Sample). The t-test compares differences in mean across the two samples, and the table reports mean, sample size, mean differences, and significance levels.

	Full Sample		**Face Sample**		
	Mean	N. Obs	Mean	N. Obs	Difference
Panel A: Company characteristics					
Firm & Team Characteristics					
Founding Year	2016.141	122,984	2016.017	80,198	-0.125***
Founding Team Size	1.833	122,984	1.862	80,198	0.029***
Ethnically Diverse	0.017	122,984	0.021	80,198	0.003***
Female-founded	0.217	122,984	0.248	80,198	0.031***
VC Financing	0.193	122,984	0.237	80,198	0.044***
Location					
CA Company	0.282	122,984	0.301	80,198	0.019***
NY Company	0.126	122,984	0.129	80,198	0.003**
MA Company	0.040	122,984	0.043	80,198	0.003***
Exit Outcomes					
Exit	0.075	122,984	0.092	80,198	0.017***
IPO	0.005	122,984	0.007	80,198	0.002***
M&A	0.070	122,984	0.085	80,198	0.016***
VC-Backed Companies					
Funding Year	2017.842	23,729	2017.576	18,967	-0.266***
N. Rounds	3.153	23,729	3.293	18,967	0.140***
First Round Size (M USD)	9.201	16,904	9.129	13,562	-0.073
Ln(First Round Size)	1.186	16,904	1.184	13,562	-0.002
Total Equity Raised (M USD)	68.839	20,549	74.769	16,573	5.931*
Ln(Total Equity Raised)	2.546	20,549	2.641	16,573	0.095***
Second Round	0.598	23,729	0.629	18,967	0.031***
Seed Stage	0.685	23,729	0.683	18,967	-0.002
Early Stage	0.212	23,729	0.217	18,967	0.005
Panel B: Founder characteristics					
Founder Age (Years)	30.762	122,984	31.270	80,198	0.508***
Education & Work Experience					
Completed by founding time					
Bachelor Degree	0.624	70,140	0.622	48,160	-0.003
Master Degree	0.194	70,140	0.201	48,160	0.007***
Ph.D. Degree	0.071	70,140	0.076	48,160	0.005***
MBA Degree	0.095	70,140	0.099	48,160	0.004**
STEM Degree	0.266	70,140	0.273	48,160	0.007**
Elite School Degree	0.112	70,140	0.124	48,160	0.013***
Missing Founder Education	0.430	122,984	0.399	80,198	-0.030***
Work experience					
Work Experience (Years)	3.269	122,984	3.852	80,198	0.583***
N. of Prev. Jobs	0.862	122,984	1.051	80,198	0.189***
Founder Experience	0.273	122,984	0.316	80,198	0.042***
CEO Experience	0.112	122,984	0.135	80,198	0.023***
C-suite Experience	0.057	122,984	0.071	80,198	0.014***
Chief Experience	0.122	122,984	0.145	80,198	0.024***
Investor Experience	0.022	122,984	0.029	80,198	0.007***
Top Employer Experience	0.019	122,984	0.025	80,198	0.006***

Table A5: Proportion of Companies by Industry Group (Crunchbase). This table presents the proportion of companies operating in each of the 49 industry groups as defined by Crunchbase (one company can be assigned to one or a few industry groups reflecting more precisely the markets it operates in). The industries are sorted in descending order of prevalence.

Crunchbase Industry Group	Share of Startups
Software	0.36
Information Technology	0.19
Professional Services	0.18
Internet Services	0.17
HealthCare	0.15
Media and Entertainment	0.15
Sales and Marketing	0.15
Financial Services	0.14
Other	0.13
Data and Analytics	0.12
Science and Engineering	0.11
Commerce and Shopping	0.11
Real Estate	0.08
Advertising	0.08
Hardware	0.08
Design	0.08
Apps	0.07
Education	0.07
Mobile	0.07
Artificial Intelligence (AI)	0.06
Community and Lifestyle	0.06
Administrative Services	0.05
Food and Beverage	0.05
Manufacturing	0.04
Transportation	0.04
Content and Publishing	0.04
Video	0.03
Privacy and Security	0.03
Lending and Investments	0.03
Sports	0.03
Biotechnology	0.03
Consumer Goods	0.03
Consumer Electronics	0.03
Travel and Tourism	0.02
Sustainability	0.02
Blockchain and Cryptocurrency	0.02
Clothing and Apparel	0.02
Payments	0.02
Music and Audio	0.02
Energy	0.02
Events	0.02
Platforms	0.01
Gaming	0.01
Navigation and Mapping	0.01
Natural Resources	0.01
Social Impact	0.01
Agriculture and Farming	0.01
Messaging and Telecommunications	0.01
Government and Military	0.01

Table A6: Proportion of Companies by Industry (Regrouped). This table presents the proportion of companies classified into seven broad industry groups based on their industry category groups in Crunchbase (CB). The assignment process is described in Appendix Table A7.

Industry	Mean Share
Biotech	0.03
Consumer Product and Services	0.23
Financial Services	0.15
Hardtech	0.03
Healthcare	0.12
Other	0.08
Software	0.36

Table A7: Broader Industry Classification. This table presents the broader industry classification for each industry group defined by Crunchbase, ensuring that each company is uniquely classified into a single broad industry class. We assign companies in broader industry classes according to the following order: Biotech, Financial Services, Healthcare, Software (excluding IT and Internet Services), Consumer Products and Services, Software (IT and Internet Services), and Other. Once a company is assigned to a broad industry class, it is not reassigned to any subsequent one.

Crunchbase Industry Group	**Broad Industry Classification**
Administrative Services	Other
Advertising	Other
Agriculture and Farming	Other
Apps	Software
Artificial Intelligence (AI)	Software
Biotechnology	Biotech
Blockchain and Cryptocurrency	Financial Services
Clothing and Apparel	Consumer Products and Services
Commerce and Shopping	Consumer Products and Services
Community and Lifestyle	Consumer Products and Services
Consumer Electronics	Consumer Products and Services
Consumer Goods	Consumer Products and Services
Content and Publishing	Other
Data and Analytics	Software
Design	Other
Education	Other
Energy	Hardtech
Events	Other
Financial Services	Financial Services
Food and Beverage	Other
Gaming	Consumer Products and Services
Government and Military	Other
Hardware	Hardtech
HealthCare	Healthcare
Information Technology	Software
Internet Services	Software
Lending and Investments	Financial Services
Manufacturing	Hardtech
Media and Entertainment	Consumer Products and Services
Messaging and Telecommunications	Software
Mobile	Software
Music and Audio	Consumer Products and Services
Natural Resources	Hardtech
Navigation and Mapping	Software
Other	Other
Payments	Financial Services
Platforms	Software
Privacy and Security	Software
Professional Services	Other
Real Estate	Other
Sales and Marketing	Consumer Products and Services
Science and Engineering	Hardtech
Social Impact	Other
Software	Software
Sports	Consumer Products and Services
Sustainability	Other
Transportation	Other
Travel and Tourism	Consumer Products and Services
Video	Consumer Products and Services

Table A8: Face Factors and the Likelihood of VC Financing - Robustness to Excluding Ethnically Diverse Companies. This table replicates the results of Table 2. The sample excludes companies defined by Crunchase as founded by non-white founders. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)		
	(1)	(2)	(3)
Trust	0.018***	0.020***	0.024***
	(0.003)	(0.003)	(0.003)
YoAt	0.011***	0.009**	0.008**
	(0.004)	(0.004)	(0.004)
Dom	0.017***	0.015***	0.013***
	(0.004)	(0.004)	(0.004)
Basic controls	Yes	Yes	Yes
Detailed controls	No	Yes	Yes
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	56,586	56,580	56,580
R-squared	0.174	0.196	0.247

Table A9: Face Factors and the Likelihood of VC Financing - Robustness to Excluding Companies with Crunchbase Profiles Created After the VC Financing. This table replicates the results of Table 2. The sample excludes companies that were added to Crunchbase after the date of the VC round announcement. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)		
	(1)	(2)	(3)
Trust	0.016***	0.017***	0.019***
	(0.002)	(0.002)	(0.002)
YoAt	0.011***	0.008***	0.007**
	(0.003)	(0.003)	(0.003)
Dom	0.008**	0.007**	0.007**
	(0.003)	(0.003)	(0.003)
Basic controls	Yes	Yes	Yes
Detailed controls	No	Yes	Yes
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	52,378	52,372	52,372
R-squared	0.117	0.130	0.161

Table A10: Face Factors and the Likelihood of VC Financing - Dummy Face Factors. This table reports linear regression estimates of the probability of receiving venture capital financing based on the founding team's average face factors (Trust, YoAt, and Dom), represented using indicator variables: whether the team's average face factor is above the median (columns (1) and (2)), in the bottom quartile (columns (3) and (4)), or in the top quartile (columns (5) and (6)). Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)					
	(1)	(2)	(3)	(4)	(5)	(6)
Trust Top50	0.018***	0.022***				
	(0.003)	(0.003)				
YoAt Top50	0.001	0.002				
	(0.003)	(0.003)				
Dom Top50	0.008**	0.008**				
	(0.003)	(0.003)				
Trust Bottom25			-0.021***	-0.023***		
			(0.003)	(0.003)		
YoAt Bottom25			-0.008**	-0.007**		
			(0.003)	(0.003)		
Dom Bottom25			-0.015***	-0.014***		
			(0.003)	(0.003)		
Trust Top25					0.011***	0.016***
					(0.003)	(0.003)
YoAt Top25					-0.009***	-0.010***
					(0.003)	(0.003)
Dom Top25					-0.002	-0.002
					(0.003)	(0.003)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year x State	Yes	Yes	Yes	Yes	Yes	Yes
Industry Group	No	Yes	No	Yes	No	Yes
Observations	57,454	57,454	57,454	57,454	57,454	57,454
R-squared	0.200	0.251	0.200	0.251	0.200	0.250

Table A11: Face Factors and the Likelihood of VC Financing - Team Gender Composition. This table reports linear regression estimates of the probability of receiving venture capital financing based on the founding team's average face factors (Trust, YoAt, and Dom) interacted with the dummy variables for whether the startup is founded by a mixed-gender team (*Mixed-gender*) or a female-only team (*Female-only*) (startups founded by male-only teams are the reference group). See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)		
	(1)	(2)	(3)
Trust	0.020***	0.021***	0.026***
	(0.003)	(0.003)	(0.003)
Trust x Mixed-gender	0.068***	0.071***	0.067***
	(0.020)	(0.019)	(0.019)
Trust x Female-only	-0.022***	-0.018***	-0.020***
	(0.007)	(0.007)	(0.007)
YoAt	0.007	0.004	0.003
	(0.005)	(0.005)	(0.005)
YoAt x Mixed-gender	0.067***	0.071***	0.073***
	(0.026)	(0.026)	(0.025)
YoAt x Female-only	0.009	0.010	0.007
	(0.009)	(0.009)	(0.009)
Dom	0.015***	0.013***	0.013***
	(0.005)	(0.005)	(0.005)
Dom x Mixed-gender	0.048*	0.052*	0.050*
	(0.028)	(0.028)	(0.027)
Dom x Female-only	-0.004	-0.007	-0.011
	(0.010)	(0.010)	(0.010)
Mixed-gender	-0.060***	-0.061***	-0.052***
	(0.008)	(0.008)	(0.008)
Female-only	-0.018***	-0.023***	-0.002
	(0.005)	(0.005)	(0.005)
Basic controls	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	57,460	57,454	57,454
R-squared	0.179	0.201	0.252

Table A12: Face Factors and the Likelihood of VC Financing - Founding Team Structure. This table reports linear regression estimates of the probability of receiving venture capital financing based on the founding team's average face factors (Trust, YoAt, and Dom) interacted with the dummy variables for whether the startup is founded by a solo founder (*Solo-founded*) (startups founded by a team are the reference group). See Appendix Table A1 for detailed variable definitions. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)		
	(1)	(2)	(3)
Trust	0.066***	0.068***	0.072***
	(0.010)	(0.010)	(0.009)
Trust x Solo-founded	-0.060***	-0.061***	-0.059***
	(0.010)	(0.010)	(0.010)
YoAt	0.037***	0.037***	0.034***
	(0.014)	(0.013)	(0.013)
Trust x Solo-founded	-0.033**	-0.037***	-0.034**
	(0.014)	(0.014)	(0.014)
Dom	0.103***	0.103***	0.093***
	(0.013)	(0.013)	(0.013)
Dom x Solo-founded	-0.107***	-0.110***	-0.099***
	(0.014)	(0.014)	(0.013)
Solo-founded	-0.248***	-0.238***	-0.204***
	(0.004)	(0.004)	(0.004)
Basic controls	Yes	Yes	Yes
Detailed controls	Yes	Yes	Yes
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	57,460	57,454	57,454
R-squared	0.168	0.191	0.243

Table A13: Face Factors and the Likelihood of VC Financing - Max Team Level Factors. This table replicates the results of Table 2 using the founding teams' maximum face factors (Trust, YoAt, and Dom). It reports linear regression estimates of the probability of receiving venture capital financing based on these maximum values. Robust standard errors are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	P(VC Financing)		
	(1)	(2)	(3)
Trust	0.072***	0.071***	0.074***
	(0.009)	(0.009)	(0.009)
YoAt	0.022**	0.017	0.014
	(0.011)	(0.011)	(0.010)
Dom	0.034***	0.035***	0.029***
	(0.011)	(0.011)	(0.010)
Basic controls	Yes	Yes	Yes
Detailed controls	No	Yes	Yes
Founding Year x State	No	Yes	Yes
Industry Group	No	No	Yes
Observations	17,847	17,803	17,803
R-squared	0.128	0.175	0.243

KU LEUVEN
Faculty of Economics and Business
Management, Strategy and Innovation (MSI)
Naamsestraat 69 bus 3535
3000 LEUVEN, Belgium
tel. + 32 16 32 67 00
msi@econ.kuleuven.be
https://feb.kuleuven.be/research/MSI/