# Leveraging Technology Expertise in Venture Capital Screening: Evidence from Start-up Competitions*


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## Abstract

Identifying innovative startups remains a critical challenge due to venture capital (VC) human capital constraints. Exploiting a prestigious startup competition where ventures were independently assessed by VCs and scientists, we find that scientist evaluations powerfully predict long-term innovation output, specifically high-citation patents, far exceeding what VC evaluations capture. Moreover, VCs are significantly more likely to invest in startups they reviewed if those startups received high scientist marks, demonstrating that investors dynamically learn from external scientific expertise once competition outcomes make it inferable. To establish external validity, large-sample PitchBook data confirms that VCs with STEM PhDs achieve superior investment outperformance, especially in high-tech sectors.



**Key words**: venture capital; screening; scientist; human capital; innovative start-up.
**JEL**: G24; J24; L26; M13; O31.



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# 1. Introduction

Venture capital (VC) is widely regarded as a key engine of technological progress, channeling capital toward startups that drive innovation and economic growth (Lerner and Nanda, 2020). Yet many of the most technologically promising ventures struggle to attract early-stage financing. This gap may partly reflect the structural incentives facing investors: venture capitalists (VCs) must balance risk and returns within the limited time horizon of their funds, creating pressure to favor opportunities with more predictable prospects over highly uncertain breakthrough ideas (Nanda and Rhodes-Kropf, 2013, 2017; Lerner & Nanda, 2020). Beyond these incentive considerations, however, a deeper informational challenge may compound the problem. Evaluating frontier technologies requires specialized scientific expertise. Startups often operate at the edge of existing knowledge, where assessing the novelty, feasibility, and potential impact of a technology is inherently difficult for investors (Aggarwal et al., 2015; Jackson and Strebulaev, 2025). In this paper, we provide empirical evidence on this evaluation friction and further investigate whether access to formal scientific expert evaluation can help identify breakthrough ventures and mitigate the financing gap.

Empirical investigation of this question has been hindered by several challenges: the lack of independent evaluations of early-stage ventures by both technological and market experts of the same early-stage ventures, limited data on start-up characteristics at the time of assessment, and scarce post-evaluation performance information for both funded and unfunded companies. We overcome these barriers by exploiting a unique institutional setting: a large-scale startup competition in Shanghai in which early-stage

high-tech ventures were independently evaluated by two distinct groups of experts, professional VCs and scientific experts.

Crucially, the two groups assess the same startups: VC judges evaluate ventures based on application materials and founder pitches, while scientist judges evaluate ventures based on application materials alone. The final competition score is a weighted average of the two groups' assessments, but individual scores remain strictly confidential — only the list of winners is publicly disclosed. This institutional design provides an unusually large-scale record of real, high-stakes evaluations linked to subsequent venture performance. At the same time, it allows us to isolate the information content of each type of expert without the confounding influence of certification effects.[1]

Our primary sample comprises 3,205 high-tech start-ups that participated in the competition across two cohorts, in 2017 and 2018. At the time of the evaluation, these startups had an average operational history of four years and 22 employees. For each startup, we combine confidential judge scores from both VC and scientist panels with rich firm-level application materials and a post-competition survey of VC judges on their investment preferences.[2] To track post-competition outcomes, we link the startup data to two comprehensive third-party databases — Qichacha and Incopat — capturing subsequent financing rounds, survival, employment growth, and innovation output

[1] Only the winners' names are announced, not their scores or rankings, reducing concerns about certification or signaling effects (Howell, 2020). By controlling for winner outcome, we further address this concern.

[2] Given the competition is government-administered, firms have strong incentives to report accurate information.

through January 2024. This gives us a robust 5-to-6-year window to observe meaningful long-term operational horizons like survival rates and patent citation maturities.[3]

We begin by examining how VC and scientist judges extract different information from the same set of ventures. For each judge type, we decompose scores into a predicted component that reflects weighting of observable firm characteristics, and a residual component capturing unobserved factors such as private signals, judge-specific expertise, or founder interactions. The modest correlation between predicted scores (approximately 0.5) indicates that the two groups weigh observable information differently, while the near-zero correlation between residuals suggests they draw on distinct private information. Observable characteristics explain a larger share of variation in scientist scores, consistent with greater reliance on codified application information, whereas VC scores show higher sensitivity to non-linear and experience-based patterns, suggesting a more complex and interactive evaluation process.

Our central finding is that scientist and VC evaluations predict fundamentally different dimensions of future venture performance, revealing a systematic divergence in what each type of expert identifies as high growth potential. Scientist scores demonstrate strong and incremental predictive power for innovation output, survival, and employment growth beyond what VC evaluations alone capture. VC scores, by contrast, are stronger predictors of a startup's subsequent financing success and commercialization outcomes. Together, these results indicate that VCs emphasize

[3] Qichacha is a leading Chinese company information query platform that provides comprehensive data on over 200 million Chinese companies, while Incopat is a global patent database platform specializing in intellectual property (IP) information that collects data from over 157 patent offices worldwide.

marketability and financial traction, whereas scientists capture underlying technological promise that translates into long-term innovation and growth. This asymmetric result highlights that technology experts capture dimensions of quality that conventional investors often miss, indicating that integrating scientific expertise can substantially improve early-stage screening of innovative start-up companies.

To investigate the mechanism behind this divergence, we examine how judge scores relate to subsequent investment decisions by VC judges themselves.[4] VC scores are strong predictors of their own subsequent investments, as expected. Scientist scores, however, have little independent predictive power for VC investment decisions. There is one revealing exception: when a VC served as a judge for a specific venture, higher scientist scores are strongly associated with a greater likelihood of that VC subsequently investing in the same firm. This pattern arises because competition outcomes are determined by the weighted average of both groups' scores. As a result, VC judges can partially infer the scientist evaluation for the specific ventures they personally reviewed. To confirm this learning channel and rule out alternative explanations like differential attention, we examine whether the increase in investment sensitivity is concentrated specifically on scientist scores. We find that the effect is driven primarily by the scientist residual component, which captures information beyond observable venture characteristics. This pattern suggests that VC judges learn from scientists' private assessments of technological quality when they can infer them

[4] As of January 2024, 31 contestant startups have secured funding from 22 distinct institutions that had sent 23 individual VC judges to the 2017 and 2018 competitions, resulting in a total of 48 investment deals.

from the competition process, rather than simply responding to observable characteristics. This finding suggests that VCs do value scientific assessments when they can access or infer them. This pattern is inconsistent with alternative explanations based on differential attention or effort allocation during the competition, pointing toward technological human capital constraints as an important barrier to the identification of highly innovative startups.

The relevance of scientific expertise is further confirmed by cross-sectional heterogeneity. The results highlight the role of technology-specific human capital, especially when VCs assess highly uncertain startups. In the artificial intelligence sector, scientist scores have markedly stronger predictive power for subsequent VC funding than in other industries, consistent with the idea that frontier innovations require specialized expertise. The advantage of scientist evaluations is also greater for younger startups, where market signals are weaker. Overall, these findings show that scientific expertise enhances early-stage screening by helping investors identify innovative firms that might otherwise be missed.

While the competition setting provides granular data on both VC and scientist evaluations, we acknowledge the potential external validity limitations it brings. Using survey evidence, we show that VC judges apply real-world investment philosophies to their evaluation of contestants during the competition. Outside of the competition, we complement our analysis with a large external sample of global VC-backed startups from Pitchbook, linking their performance to the educational

backgrounds of investors. From 2007 to 2015 worldwide, ventures backed by VCs with STEM PhDs significantly outperform those backed by investors without such training. Although consulting technical experts is common in investment practice, our large-sample evidence provides an opportunity to examine whether technological expertise is associated with investment outcomes outside our institutional setting. To address the concern that VCs with STEM PhDs may simply sort into particular industries, we compare performance across sectors. We find that the performance differential is concentrated in technology-intensive sectors and is largely absent in business and financial sectors. This pattern is consistent with the notion that technology-specific human capital is particularly relevant in the evaluation of technologically complex ventures and lends external support to our interpretation of the competition-based evidence.

Our paper contributes to four strands of literature. First, we contribute to the literature on the role of VCs in promoting innovation. While previous work links VC investments to improved innovation outcomes (Kortum and Lerner, 2000, 2001; Gornall and Strebulaev, 2021), recent studies highlight limitations in the allocation of VC funding to major technological advances, especially during economic downturns when VCs may prioritize more profitable, less innovative firms (Ewens et al., 2018; Howell et al., 2020; Lerner and Nanda, 2020). Our findings provide micro-level evidence that VCs face constraints in evaluating technological potential during early-stage screening. Specifically, we show that scientific expert evaluations predict future innovation, survival, and employment growth beyond what VC assessments capture.

Second, our work extends the literature on VC expertise and human capital. Prior studies examine how investor characteristics, such as experience, networks, and background, shape venture outcomes (Lerner, 1994; Nahata, 2008; Hsu, 2004; Sørensen, 2007; Gompers et al., 2016, 2020, 2022; Bottazzi et al., 2008; Zarutskie, 2010), with more recent work highlighting the role of technology competence and sector-specific knowledge in screening (Aggarwal et al., 2015; Scott et al., 2019; Jackson and Strebulaev, 2025). We push this agenda further by examining how distinct forms of human capital shape the evaluation of the same ventures. Leveraging independent assessments of identical firms, we provide micro-level evidence that scientific expertise captures dimensions of venture quality, particularly future innovation output and survival, that financial expertise systematically misses. Our large-sample PitchBook analysis reinforces this at scale: embedding technological expertise within a fund is associated with superior long-run investment performance. Taken together, these findings complement existing explanations for underinvestment in frontier innovation, ranging from VC market structure and financing constraints to the increasing reliance on algorithmic screening (Lerner and Nanda, 2020; Nanda and Rhodes-Kropf, 2013, 2017; Krieger et al., 2023; Lyonnet and Stern, 2022; Bonelli, 2023).

Third, our paper contributes to research on how VCs use information in investment decisions. Existing work documents that investors rely on accounting data and team attributes to select and monitor ventures (Gompers and Lerner, 2001; Kaplan and Strömberg, 2001; Armstrong et al., 2007; Davila and Foster, 2007; Cassar, 2009;

Beuselinck et al., 2023). We extend this literature in two directions. First, we show that VCs systematically place less weight on observable technological attributes than scientific experts do and rely more heavily on financial indicators such as past funding and near-term profitability. This pattern is consistent with the presence of technological human capital constraints in venture screening. Second, we demonstrate that this gap is not fixed: when scientific assessments become inferable from competition outcomes, VC judges actively incorporate them into subsequent investment decisions. Taken together, these findings suggest that the underutilization of technology-related signals in early-stage screening reflects a human capital constraint and this friction can be alleviated when the scientific knowledge becomes accessible.

Finally, we contribute to the literature on new venture competitions as emerging intermediaries for early-stage startups (Howell, 2020). Prior research has focused on accelerators, incubators, and crowdfunding (Hochberg and Fehder, 2015; González-Uribe and Leatherbee, 2018; Yu, 2020; González-Uribe and Reyes, 2021), but competitions remain underexplored despite their global growth. Using a setting with both VC and scientist judges, we show how evaluator expertise shapes startup screening and the effectiveness of intermediary selection mechanism.

The remainder of the paper is organized as follows: Section 2 introduces the institutional background of the competition. Section 3 describes the data and sample. Section 4 presents the empirical methodology. Section 5 demonstrates the predictability of judge evaluations on ventures' subsequent performances. Section 6 examines the

heterogeneity. Section 7 provides robustness tests. Section 8 discusses the external validity. Section 9 concludes.

# 2. Institutional Background

## *2.1. Startup in Shanghai Competition*

The China Innovation and Venture Competition, organized annually by the Ministry of Science and Technology since 2012, is the largest of its kind in the country. Our data come from the "Startup in Shanghai" regional-level tournament, which consists of district-level competitions for companies registered within the respective district. The participating firms in Shanghai are distinctly characterized by high-tech, high-growth, and high-value-added, with 91.49% of the entities specializing in core hard-tech sectors. Over the years, the competition incubated 80 listed companies, with 30 on the Shanghai Stock Exchange Science and Technology Innovation Board (STAR Market) by the year of 2021.[5] Contestants are classified into "small & micro" and "growth-stage" ventures based on revenues and number of employees. We focus on the "small & micro" venture group that competed in Shanghai's Pudong New District in 2017 and 2018 owing to data availability.

Pudong New District is the largest district in Shanghai by economic activity during our sample period. As a state-level new district, Pudong receives special government support and has developed world-class industrial clusters in integrated circuits,

[5] IPO numbers are obtained from the "Startup in Shanghai Thrive in the Future" report. Since its launch, the STAR Market has supported the public listing of 589 "hard-tech" enterprises (as of mid-2025). Highlighting the market's regional concentration, 93 of these firms are based in Shanghai (https://jrj.sh.gov.cn/ZXYW178/20250723/12d98ecc2f1b415eba272ff6acca74a9.html).

biomedicine, and artificial intelligence. These advantages have established it as a dynamic hub for technology entrepreneurship, which is reflected in our sample's industry composition. Specifically, ventures span eight distinct industry groups: new materials, electronics and information, Internet and mobile Internet, advanced manufacturing, new energy and energy efficiency, biotechnology and pharmaceuticals, technology service, and culture and creativity.

"Small & micro" venture group adheres to specific participation criteria: (i) annual revenue of no more than 30 million RMB; (ii) employment of no more than 300 people, with at least 10% engaged in R&D; and (iii) an R&D-to-income ratio of at least 5% in the preceding fiscal year. "Startup in Shanghai" competition consists of a single round and the winners receive a 200,000 RMB grant (half from a municipal InnoFund (Bian et al., 2022) and half from a district-level match).[6]

To understand the motivation for participation, we surveyed all ventures that competed in 2018. With a 62% response rate, we show that the primary motivation was to secure the grant (87% of respondents), followed by enhancing reputation (71%), and receiving feedback from judges (68%). Our interviews with 20 founders further confirmed that the certification from a government-backed competition is more valuable than the modest monetary award (200,000 RMB, compared to the average income of 3.7 million RMB). The certification improves reputations, facilitates access to low-interest loans, and enhances connections with VC investors (Howell, 2020).

[6] Each year, a small number of the top-ranked winners advance to the national-level competition. For example, in 2017, only 18 out of the 1,699 in the small & micro venture group qualified to participate in a national-level competition.

Upon signing up, all contestants are required to submit detailed firm information to a government-maintained platform, including firm registration, team composition, technology or product, financials, and business plans (See Appendix A). Our examination of submissions from ventures participating in 2017 and 2018 reveals that 9.5% had secured equity funding and 2.3% had received debt funding prior to the competition.

*2.2. Judges and Evaluation Procedure*

The competition employs a unique dual evaluation system, with ventures assessed by two independent groups of judges. First, two technology-oriented reviewers are assigned to each venture to evaluate its potential and technical feasibility. These reviewers are randomly selected from a repository of experienced academics or industry researchers maintained by the Science and Technology Commission of Shanghai Municipality (STCSM). Eligibility for inclusion in the repository requires holding a position of associate research fellow or research fellow, serving as the principal investigator for a grant project funded by a provincial-level science & technology commission or national research institutions, or receiving provincial or national science and technology awards.[7] Reviewers are matched to ventures by industry field. They have access to the ventures' full application packet, and their identities remain confidential to the contestants.

[7] The Chinese version of the announcement can be accessed at: http://www1.shanghaiinvest.com/cn/viewfile.php?id=13368.

The second group is a three-person panel of professional VC or angel fund investors, who are randomly selected from a large pool of VCs.[8] VC judges are highly educated (over 80% with master's degrees) and experienced professionals (over half with over eight years of experience) primarily from high-caliber VC funds known for significant fundraising and successful IPO exits. Panels are randomly assigned to ventures according to the judges' industry expertise. Judges have access to the application packet and, crucially, attend a 15-minute pitch presentation. The VC judges and contestants do not know each other's identities in advance. All judges score projects independently without discussion.

A venture's final score is a weighted average of the two scores: 40% comes from the technical experts, and 60% comes from the VC judges. An additional 1 to 3 bonus points are added based on specific, pre-determined criteria like sales growth. Contestant ventures are aware of the bonus points but are not informed of the exact criteria. As researchers, we have access to both the bonus criteria and which ventures received these points. Given that bonus points account for a small portion of the total score (1-3 points out of 100), they are fairly distributed and do not appear to influence the likelihood of winning.

The list of winners is publicly announced by the STCSM, and about one-third of the ventures with highest scores receive a grant in the Pudong District competition. Importantly, the final scores and rankings are kept confidential from all competition

[8] Importantly, serving as a competition judge was a service role rather than a recruitment activity for talent selection, ensuring that their evaluations remained objective and free from proprietary pipeline incentives.

participants and judges. Winners are only informed of their winning status, not their score or rank.

# 3. Data and Sample

Our analysis relies on a unique combined dataset. The core of the data is drawn from internal administrative records of the competition, which includes firm-level application information, core team member resumes, and confidential evaluation records. These records provide details on pitch-day judge assignments, including raw scores from both scientist and VC judges, bonus points, final total scores, and winner status. To measure post-competition outcomes, we supplement the internal data with information from external databases. Qichacha, a comprehensive Chinese company information platform, is used to track subsequent funding events, employment and survival. For innovation output, we retrieve data on patents and citations from Incopat, a global intellectual property database. Additionally, we use proprietary data from a survey of the VC judges, which was administered on the same day of the pitch competition to capture their preferences and evaluation criteria.

## *3.1 Application Information*

Upon the application, startups in the competition provided key financial and economic data via an electronic platform (see Appendix A for details). We use this data to analyze 3,205 participating startups from the 2017 and 2018 competitions in the Pudong District. As shown in Table 1, the top three industries are “Internet and Mobile”,

"Electronic Information" and "Advanced Manufacturing", with a notable difference in the industry distribution between 2017 and 2018.

The participating firms are generally young and small. About 75% are less than five years old with fewer than 26 employees. The median firm is three years old with 15 employees. Medians for total assets and total liabilities are 1,627,000 RMB (approx. 229,200 USD) and 58,000 RMB (approx. 8,170 USD), respectively. Receivables and inventory are minimal, as most startups do not even have production lines at this stage. The relative low level of tangible assets represents the innovative nature of the high technology startups alike.

Despite this small size, the firms are highly innovative, with a median R&D expense of 892,000 RMB (approx. 126,000USD). Most firms have negative net profit, with a median of -157,000 RMB (approx.-22,060 USD). This is likely due to high operating expenses rather than inefficient production process, as most have positive gross profits. This pattern is consistent with the significant R&D and professionalization costs for early-stage startups.

Following Kisseleva, Mjøs, and Robinson (2024), we disaggregated book equity into cumulative capital, retained earnings, and current profits. We further break down current profit/loss into gross profit/loss and expenses.[9] Table 1 presents summary statistics of these variables, aligning with the cash flow lifecycle of early-stage firms

[9] These include operating, administrative, capital, R&D, and non-operating expenses. Another deductible item in the calculation of net profit is the income tax. In the results shown, the variable "Expenses" includes income tax to ensure the disaggregation equation of book equity holds. The regression results are similar in sign and magnitude if we exclude income tax from "Expenses".

which often have positive gross profits but negative cash flows and retained earnings due to high expenses.

We also assess technology stack by collecting information regarding the human capital and intellectual property. About 75% of participants have no patent nor software copyrights at the time of the competition. At the median, nine of 15 employees are engaged in R&D, and 13 hold college degrees or higher, indicating a strong presence of knowledge-intensive human capital.

The application form also includes founder demographics. The average founder age is 39, with 92% holding a degree above the bachelor's and 53% having a master's or PhD. Additionally, 22% have studied abroad, and more than 50% are serial entrepreneurs.

*3.2 Judge Scores*

We have access to confidential administrative records of the evaluation scores (average scores from scientist and VC judges, as well as bonus points), final total scores, and winner status, and ranking information from the 2017 and 2018 competitions. The average score from VC judges is 74.43 (with a standard deviation of 9.20), while scientist judges have an average score of 75.39 (with a standard deviation of 9.60). As an initial check, we examine the correlation between the scores given by the two types of judges. As shown in Figure B.1 in Internet Appendix, the correlation coefficient is around 0.25. This suggests that while VC and scientist judges share some common

perspectives in their evaluations, a substantial portion of the scores is driven by distinct factors unique to each judge group.

*3.3 Post-Competition Performance*

We track the post-competition performance information of firms in the sample up to January 2024. The variables are classified into two categories: real performance and fundraising. Real performance is captured by innovation outputs, including patent applications and citations, grants, technical certificates, software copyrights, and scientific awards. We also measure survival and growth using employee counts recorded in Qichacha. We use VC financing deals to measure fund raising outcomes. In addition, we collect data on trademarks, which often signal product commercialization (Chemmanur et al., 2023).

Table 2 summarizes the post-competition venture performances. Innovation activities are pervasive among these startups. Since the competition, 45% of the startups have applied for a patent. Even when excluding applications made before the first VC funding, 42% have still filed patent applications. Additionally, 47% of the startups have been awarded professional or technical certificates, 54% have secured software copyrights, and approximately 44% have received national or regional scientific awards. Regarding financing and commercialization, 12% of these startups have secured at least one VC financing deal, and around 43% have registered at least one trademark. In terms of real performance up to January 2024, we observe that the average survival rate is 0.86, with average employment number of 17.28.

*3.4 Survey on VC Judges*

To better understand the VC judge's investment rationale, we conducted a survey of VC judges to understand their backgrounds and evaluation criteria.[10] Out of 307 VC judges, we received 221 responses who work in 162 distinct VC firms. To ensure impartiality, all information was anonymized. We also observe 82 financing deals in which at least one investing institution matched a VC judge's firm.

The survey responses reveal that VCs prioritize a startup's founding team, product & technology, and market prospects. By contrast, they rate financials and intellectual property, two areas with rich data in the application, as least important. We also find that 60-65% of VC judges were assigned to their preferred investment sector in competition. While the survey indicates that VCs explicitly state they prioritize a startup's product and technology, our subsequent quantitative analysis reveals they often place less weight on underlying technical potential relative to financial metrics. This tension suggests that while VCs aspire or claim to screen for technical quality, they face structural human capital constraints that prevent them from doing so accurately without external scientific expert benchmarks.

Demographic information of VC judges shows that more than 80% have at least a master's degree. They also had significant experience in the financial industry, with over 90% having worked in the industry for more than four years, and 50% for over eight years. The institutions represented by these VC judges reflect the broader

[10] Please find the complete and detailed survey instrument in Appendix A.2. Appendix C includes the VC judge survey's results and show the alignment between VC judges' scoring and their investments in the real world.

landscape of investors interested in young, innovative startups. Most of them are VC funds, alongside some angel investors and a small number of private equity investors. Over 50% of these institutions raised more than 200 million RMB (28 million USD) in the past three years, and about half have achieved successful exits via IPO.

# 4. Empirical Methodology

*4.1 Decomposition of Judge Scores*

To examine whether scientist judges could help VCs better identify innovative startup companies, we decompose the scores into two independent components. Following previous studies that highlight the roles of public and private information in financing decisions (e.g., Armstrong et al., 2007), we hypothesize that startup evaluations are shaped by both observable information in the application forms and private information held by the judges. The application materials provide detailed and comprehensive "hard" information commonly used in screening, while different experts may draw on their own experience, networks, or domain knowledge to incorporate additional insights.

Scientists may complement VCs' judgments in two ways: by processing the same observable information differently and by contributing additional private information. To capture these two elements, we formally decompose a judge's evaluation score using following equation:

$$Score_{i,t,\boldsymbol{p}} = f(X_i) + \mu_{t,\boldsymbol{p}} + \varepsilon_{i,t,\boldsymbol{p}}, \quad (1)$$

where $i$ denotes the participant venture, $t$ is the competition year, and $p$ represents group identifiers (i.e., industry group and VC judge panel). $f(X_i)$ describes the relationship between $Score_{i,t,\boldsymbol{p}}$ and the rich set of application information $X_i$ for participant $i$. Different functional forms indicate varying methods of processing the information. We experiment with different specifications of the functional form $f$ within the class of polynomial functions, where higher-order polynomials represent more complex methods of processing the information in $X_i$. $\mu_{t,\boldsymbol{p}}$ represents fixed effects corresponding to the competition year, industry group and judge panel.

This decomposition separates each judge's score into two parts. $f(X_i)$ is the common perception based on observable characteristics, where "common" indicates that both VC and scientist judges apply the same approach $f$ to process the information in $X_i$. The second component, $\varepsilon_{i,t,\boldsymbol{p}}$, captures the judge's individual evaluation based on private information. While $\mu_{t,\boldsymbol{p}}$ accounts for factors that are not specific to startups that explain a significant share of score variation, it is not the focus of our analysis.

We conduct several tests (reported in Appendix B) to examine the methods applied by the two judge groups. First, to test how different judges process hard information, we estimate coefficients to a given characteristic $x_i$ under the same specification of $f(.)$. In general, the coefficients differ (shown in Figure B.2): VC judges reward higher equity raised, gross profits, and even losses, showing openness to ventures at different financial stages; they also favor higher expenses, though the link to retained earnings is weak. In contrast, scientist judges value raised equity and gross profits but place no weight on retained earnings and respond positively only to lower expenses,

likely due to concerns about near-term cash flow. Second, we show that scientists process common information differently from VC judges. The correlation coefficient between the predicted scores $\hat{f}^{VC}(X_i)$ and $\hat{f}^{Tech}(X_i)$ is only 0.5, suggesting great divergence in how the two groups processing the same information. We further compare the adjusted R-squares (goodness-of-fit) for the regression model (1) under different specifications of $f(.)$. As shown in Figure B.3, the fit for VC scores improves with higher-order polynomials, whereas the adjusted $R^2$ for scientist scores remains largely unchanged. This pattern suggests that scientists rely on simpler, more structured approaches, while VCs employ more flexible, experience-driven heuristics. Scientists' distinct perspective may therefore complement VC screening, particularly when VCs overweight certain features or process information in overly complex ways. Finally, we assess whether scientist judges might bring in private information unavailable to VC judges. The correlation between $\hat{\varepsilon}_{i,t,p}^{VC}$ and $\hat{\varepsilon}_{i,t,p}^{Tech}$ is close to zero, suggesting the two judge groups' private information sets are largely independent. Thus, any correlation in their total scores arises from shared application materials, albeit processed differently, rather than overlapping private information. This evidence indicates that scientists could contribute additional, independent insights to the evaluation process.

*4.2 Evaluation and Venture Performance*

We next examine how judge evaluations relate to the post-competition performance of participating startups. While both groups of judges may possess the ability to identify ventures with high innovation potential, as the VC industry increasingly integrates STEM-trained experts, differences in evaluators' expertise become more salient. We

therefore expect scientist judges to be better at identifying startups with strong real outcomes, especially innovation output, while VCs remain more accurate in predicting subsequent financing success. It is also possible that neither group's scores predict post-competition performance. Judges' evaluations may fail to reflect their true opinions if they exert limited effort, if accurate evaluation is costly, or if they have incentives to please competition organizers by giving consistently high marks. In addition, the competition environment may differ from judges' typical investment settings, potentially inducing behavioral biases.

To test the predictive power of judges' evaluations, we estimate the following regression model that relates evaluation scores to multiple post-competition performance measures :

$$Y_{i,t,\boldsymbol{p}} = \beta Score^{VC}_{i,t,\boldsymbol{p}} + \mu_{1,t,\boldsymbol{p}} + e_{1,i,t,\boldsymbol{p}}$$

$$= \beta Score^{VC}_{i,t,\boldsymbol{p}} + \gamma Score^{Tech}_{i,t,\boldsymbol{p}} + \mu_{2,t,\boldsymbol{p}} + e_{2,i,t,\boldsymbol{p}}$$

$$= \beta_1 \hat{f}^{VC}(X_i) + \beta_2 \hat{\varepsilon}^{VC}_{i,t,\boldsymbol{p}} + \gamma_1 \hat{f}^{Tech}(X_i) + \gamma_2 \hat{\varepsilon}^{Tech}_{i,t,\boldsymbol{p}} + \mu_{3,t,\boldsymbol{p}} + e_{3,i,t,\boldsymbol{p}}, \quad (2)$$

where $Y_{i,t,\boldsymbol{p}}$ is a set of post-competition outcome variables for the participant startup $i$ in the year of competition $t$. $\boldsymbol{p}$ is a set of group identifiers, including industry group and the judge panel.

Our benchmark analysis examines the predictability of VC scores on startup performance. The specification only includes the VC score as the key explanatory variable. An insignificant estimate of $\beta$ would suggest that VC judges fail to identify startups with strong potential. The second specification adds the scientist-judge score,

allowing us to test whether scientific evaluations provide incremental predictive power; a significant coefficient on $\gamma$ would indicate that scientists contribute information beyond what is captured by VC assessments. Finally, we decompose both VC and scientist scores into their predicted and residual components to analyze which source of information—observable or private—drives predictability. A significant coefficient on the predicted components would imply that market participants value publicly available signals of quality, whereas significance in the residual components would point to the economic relevance of judges' private assessments. All score variables are standardized by their sample standard deviations so that coefficients represent the effect of a one-standard-deviation change in the score on the outcome variable.

Regarding the outcome of receiving subsequent financing, if post-competition investments by the broader VC market are consistent with judges' assessments during the competition, we should observe that evaluation scores predict future fundraising success.[11] A significant relationship between VC judges' scores and future funding would imply that VC assessments reflect the preferences of the wider VC community. At the same time, a positive association between scientist scores and future funding would suggest that scientific evaluations provide complementary information that the broader VC market subsequently incorporates into investment decisions. From an economic perspective, the extended specification shows whether private assessments, especially scientists' technological insights, contain information that markets later

[11] We excluded the ventures (i.e., a total of 53) who received funding from investors who acted as judge in the competitions.

value, or whether predictability stems mainly from observable venture characteristics that both experts and investors already recognize.

*4.3 VCs' Evaluation and Investment*

To better understand the underlying reasons of asymmetric predictability of VC judge and scientific judge evaluations, we narrow down our analysis to subsequent investment from VC firms that competition VC judges are affiliated with.

Our analysis sample consists of all potential pairs of VC judges' affiliated institutions and competing ventures, where an investment could, in principle, occur. The dependent variable equals one if a VC judge's affiliated institution subsequently invests in the venture and zero otherwise. In practice, only 53 of the 3,205 competing ventures receive such investment. Given this low frequency, we scale the dependent variable by its unconditional sample mean. The regression model is as follows:

$$Y_{i,t,\boldsymbol{p},m} = \beta Score_{i,t,\boldsymbol{p}}^{VC} + \gamma Score_{i,t,\boldsymbol{p}}^{Tech} + \mu_{i,t,\boldsymbol{p}} + \theta_{t,m} + e_{i,t,\boldsymbol{p},m.} \quad (3)$$

Unlike the model (2), model (3) is estimated at the investor ($m$)-startup ($i$) level. Accordingly, in addition to the regressors from model (2), we include competition year-VC firm level fixed effects to account for heterogeneity in VC firms' tendencies to invest in each cohort of competitors. Furthermore, we control for the competition outcomes (whether a competing venture $i$ was winner), competition year and other group-level variables in $\mu_{i,t,\boldsymbol{p}}$. We also analyze the sensitivity of VC judges' investments to both the predicted and residual components of the evaluations.

Next, we zoom in to look at whether VC judges invest differently in startups they personally evaluated during the competition. The random matching between judges and ventures makes this variation quasi-exogenous: for a given investor, direct exposure provides additional information—particularly regarding scientific assessments inferred from the competition outcomes—that is otherwise unavailable.

We estimate the following model to test this mechanism:

$$Y_{i,t,\boldsymbol{p},m} = \left[\beta_J \mathbb{1}\left(J_{i,m}=1\right) + \beta_{NJ}\mathbb{1}\left(J_{i,m}=0\right)\right] Score^{VC}_{i,t,\boldsymbol{p}} + \left[\gamma_J \mathbb{1}\left(J_{i,m}=1\right) + \gamma_{NJ}\mathbb{1}\left(J_{i,m}=0\right)\right] Score^{Tech}_{i,t,\boldsymbol{p}} + \mu_{i,t,\boldsymbol{p}} + \theta_{t,m} + e_{i,t,\boldsymbol{p},m.} \quad (4)$$

In this specification, $J_{i,m}$ equals one if investor $m$ evaluated startup $i$ during the competition and zero otherwise. For each score component, we estimate separate coefficients for judged (indexed by $J$) and non-judged (indexed by $NJ$) startups to capture how sensitivity to evaluation scores changes with direct exposure. The identification exploits the fact that when a VC judge evaluates a startup, she observes her own assessment and subsequently observes the competition outcome, which is a known weighted aggregation of VC and scientist scores. Although scientist scores are not disclosed, conditional on her own evaluation, the win–loss outcome provides information about otherwise unobserved components of the final score. In particular, because scientific evaluations enter the final index with a positive weight, a VC judge

can partially infer the technological assessment by comparing her own score with the realized outcome (see Appendix F for a formal model and derivation). [12]

Note that since each VC judge scores independently, when she evaluates startup $i$ she subsequently observes only the competition outcome — a known weighted average of all VC and scientist scores — but not the individual components. This means winning status reveals a composite signal that includes both the scientist's private assessment and the average assessment of the other VC judges on the panel. One might therefore be concerned that the learning we document reflects VCs updating on their peers' opinions rather than on scientific quality. However, if peer-VC learning were the dominant channel, the residual VC score should become more predictive of investment for judged ventures, since winning also reveals information about other VCs' private assessments.

We therefore expect a VC judge's investment decision to become more sensitive to the technological component of evaluations for startups she personally reviewed. In our specification, this implies $\gamma_J > 0$.

Importantly, the competition outcome may also reveal information about the assessments of the *other* VC judges. A positive and significant $\beta_J$would be consistent with such peer-VC learning. Our primary interest, however, lies in $\gamma_J$. A significantly positive $\gamma_J$, coupled with no comparable increase in sensitivity to the VC component,

[12] Note that since each VC judge gives their own score independently, they update the evaluation of other VC's score and scientist score of the startup company they themselves reviewed, given the winning status, which is publicly available.

indicates that VCs selectively incorporate scientific information—though imperfectly inferred—when they have direct exposure to the startup.

By contrast, alternative explanations based on greater attention, familiarity, or post-competition effort would predict heightened sensitivity to all evaluation components for reviewed startups. The asymmetric pattern in which only the technological component exhibits increased sensitivity therefore supports a learning-from-science interpretation rather than generic attention or effort effects.

In an extended specification, we replace the raw scores with their predicted and residual components to separate responses to public and private information. The key term is the interaction between the judged dummy and the residual scientist judge score.

# 5. Results

This section presents the predictability of VC and scientist scores on a venture's long-term innovation, survival and employment growth, their financing and commercialization outcomes. In particular, how these evaluations are linked to actual investments made by VC judges after competition.

## *5.1 Judge Evaluation and Real Performance*

As described in Section 4.2, we examine the long-term predictive power of judge scores on various innovation outcomes, utilizing data spanning up to January 2024. We begin with patent applications and citations. For each outcome, we analyze both the extensive margin (i.e., the likelihood of achieving the innovation outcome) and the intensive margin (measured by the logarithm of the outcome counts).

Table 3, Panel A presents the results for patent applications. VC judge scores show a positive and significant association with both the likelihood and the number of patent applications (columns (1) and (5)). When the VC score is decomposed, both the predicted and residual components remain significant for predicting patent application number (columns (3)), however, the residual component becomes insignificant for patent number prediction (column (7)). Notably, when both judges' scores are included in the same regression, scientist scores provide additional predictive power for future patent applications (columns (2) and (6)). The decomposition analysis further underscores this difference: while the predicted part of VC score shows significant predictive power, the predicted component of scientist score exhibits larger coefficients (Column (8)) and is highly significant across all metrics.

Panel B of Table 3 examines the number of high-citation patents and the average patent citations as proxies for patent quality. We consider all forward citations received by patents filed by a venture up to January 2024. High-citation patents are defined as the patents with above the median citation numbers within their patent class, conditional on receiving at least one citation in a given year (Babina et al., 2023). The average citation number is calculated as the total number of patent citations divided by the total number of patents granted in the same time window. Our findings reveal that VC judge scores fail to predict the average citation number, as indicated by the insignificant coefficients on the VC judge scores (column (5)). However, when the VC score is decomposed, the component based on observable information consistently shows significant predictive power for both total number of patents, and of high-citation

patents. Importantly, scientist scores significantly predict both the number of high-citation patents and the average citation count, even after controlling for VC judge scores (columns (2) and (6)). Columns (4) and (8) show that not only the predicted part of the scientist score, but also the residual component, strongly predicts patent quality, indicating that the scientist's unique, non-observable assessment is key to predicting high-quality innovation.

In Panel C of Table 3, we further examine venture survival and long-term growth, as measured by their employment. Regarding startup survival, the VC judge score exhibits a positive and significant association only when considered in isolation (column (1)); this significance disappears once the scientist judge score is included (column (2)). Conversely, the scientist judge score is a consistently significant and positive predictor of survival across all specifications that include it. The decomposition analysis further reveals that the residual of scientist score is strongly predictive of survival (column (4)), suggesting scientists capture unobservable, high-value information. Regarding employment growth, both the VC judge score and the scientist judge score are strong, positive, and highly significant predictors of the logarithm of employment. The decomposition analysis highlights that the predicted component of both the VC judge score and the scientist judge score are the primary drivers of this predictive power (column (8)). This indicates that the ability of both VCs and scientists to assess observable firm characteristics is crucial for predicting long-term employment growth.

Taken together, results in Table 3 highlights the unique ability of scientists to identify startups with high innovation outputs, higher survival probability, and greater employment growth in the long run.

### *5.2 Judge Evaluation and Financing*

We analyze how judge scores predict future funding and commercialization. Panel A of Table 4 shows that VC judge evaluations are positively associated with both the probability and number of future VC investments. In contrast, scientist judge scores do not significantly predict future VC financing (columns (2) and (6)). When the VC score is decomposed, its predicted component is substantially more influential than the residual component, exhibiting a coefficient approximately five times larger (columns (3) and (7)). To address the concern that VC judges' evaluation may be affected by their intention to subsequently invest in the companies after the competition, we exclude deals involving VC judges' affiliated institutions and results remain robust as detailed in Section 7 and Table E.1.

We also examine trademarks acquired by startups after the competition as a proxy for product market performance and financing potential, building on previous work linking trademarks to VC investments and IPO success (Block et al., 2014; Chemmanur et al., 2020). We find that higher VC judge scores strongly predict a larger number of new trademarks (Panel B of Table 4). In contrast, scientist scores do not show robust significance in predicting trademarks (columns (2) and (6)). The predictive power of VC scores remains strong when both scores are included in the regression, while the

incremental explanatory power of scientist scores for trademarks is minimal (columns (4) and (8)).

Taken together, the asymmetric findings across Table 3 and Table 4 lead to two main conclusions. First, VC judge scores likely mirror the broader VC industry's evaluation of startups, evidenced by their strong predictability of both funding and commercialization outcomes. Second, VCs in general (encompassing both the judges and the broader market) do not align their evaluations of innovative ventures with the perspective of scientist judges, despite the demonstrated ability of scientists' scores to predict superior future innovation output, survival, and long-term employment growth.

### *5.3 Do VC Judges Invest in the Competing Ventures?*

The limited predictive power of scientist judge scores for general VC investments raises a compelling question: why does this valuable assessment not translate into real-world investment decisions? To explore this, we restrict the outcome variable to investments made by VC judges.

The results are presented in Table 5. We find that a higher VC score is consistently associated with a greater likelihood of subsequent funding from a VC judge, regardless of the inclusion of the scientist judge score (columns (1) and (2)). In contrast, the scientist judge score shows no significant predictable power over the VC judge's investment decision (column (2)). In fact, the predicted component of the scientist score exhibits a negative and significant coefficient (column (4)), suggesting that the qualities captured by the scientists' observable assessments—despite their strong prediction of

startup innovation and growth in Table 3—are not prioritized by VC judges when making their own investment choices.

This misalignment may reflect a fundamental disparity in the evaluation criteria and objectives between the two groups. Specifically, VCs may prioritize metrics related to portfolio returns and immediate commercialization success, while scientists focus on long-term innovation potential and real-world outcomes. Alternatively, the disparity may arise because VCs lack the specialized technological or scientific human capital necessary to accurately evaluate the deep innovation potential that scientists are uniquely able to identify. It is also possible that VC judges may also have limited attention or are time-constrained to conduct in-depth assessments of technology.

To shed light on the possible reasons behind this contrasting pattern, we compare a VC's investment decisions for ventures they personally judged against those they did not, as described by the interaction terms in equation (4). Table 6 shows that the predictability of scientist scores is conditional: they are positively and significantly related to investment by a VC only when that VC actually served as a judge for that venture. This effect primarily originates from the residual component of the scientist judge score (column (2)). The predictive power of the scientist score weakens for ventures the VC did not review, suggesting that VCs do not fully incorporate these evaluations when they lack direct exposure.

A potential concern is that $\gamma_J > 0$ reflects greater post-competition effort or due diligence by judges toward startups they previously evaluated. However, this

interpretation would imply stronger responsiveness to all information components, including their own residual scores. In contrast, the interaction between the judged dummy and the residual VC score is insignificant, while the corresponding term for the residual technological score is positive and significant. This asymmetric pattern indicates that VCs selectively incorporate the scientific information once they gain direct access to it, a finding consistent with learning mechanism rather than general attention or effort effects.

The findings thus strongly suggest that VCs are willing to consider scientist evaluations when given access, but they face constraints in acquiring and processing this information for all ventures. For those they personally reviewed, they can infer scientist judges' evaluations by comparing their own scores to the venture's overall competition outcome. Altogether, this additional predictive power of scientists' evaluations points to that technology-proficient human capital constraints—rather than preference differences or overconfidence—limit VCs' screening of innovative startup companies.

# 6. Heterogeneous Effects on Future Venture Performance

This section extends the analysis by investigating scope of this technological human capital constraint and how the predictive power of VC and scientist judges' scores for future venture performance varies across industries, and startup characteristics.

We build on the premise that effective ventures screening requires sector-specific knowledge, which creates human capital constraints that vary by industry (Scott et al.,

2019). Our sample includes startups in eight distinct industries: Internet & Mobile (Int. & Mobile), Electronic Information (Electr. Info.), Advanced Manufacturing (Manufac.), Biotech, New Energy, Advanced Materials, Technology Service (Tech Service), and Artificial Intelligence (AI). As detailed in Panel A of Table 1, the industry distribution of contestants varies across competition years. Despite this variation, the average VC and scientist scores remain largely consistent across industries (Figure D.1 in Appendix D).

We first analyze the predictive power of scores within each industry. As shown in Figure 1, we estimate the predictive power of VC and scientist scores separately and plot the coefficients with their 90% confidence intervals for both the VC scores (blue bars) and the scientist scores (grey bars). Consistent with our main findings, higher VC scores are associated with a higher number of post-competition VC deals across most industries. Conversely, scientist scores demonstrate strong predictive power for patent applications in nearly all industries.

Figure 2 presents the predictability of the decomposed VC and technology scores (predicted values and residuals components). The predicted VC scores remain significant predictors of future VC deals in most industries, with the notable exception of the Manufacturing and AI industries. The residual scores from VC judges significantly predict future financing in the Internet & Mobile, Electronic Information, New Energy, and Material industries. In contrast, the residual scores from scientist judges are strong predictors of future financing deals only in the AI industry.

For innovation outcomes, the predicted scores from both VC and scientist judges are associated with patent applications across most industries, whereas the residual scores only predict future patent applications in the Services & Tech and AI industries. A key divergence emerges in the AI sector. Only the residual scores of scientist judges significantly predict future financing deals, while VC scores lose their predictive power. This divergence likely reflects the ambiguity and complexity of nascent technologies in the AI space, where scientific expertise provides unique, unobservable information not readily accessible to VCs during standard pitch evaluations. Our results suggest that in the AI sector, VC investors could significantly benefit from incorporating the unique insights of scientific experts.

We next investigate how the predictability of judge scores varies with start-up characteristics, focusing on founder backgrounds (Panel A of Table 7). Since founder information is available to all judges, it is already factored into the predicted scores. Therefore, our analysis centers on whether the residual component of the scores exhibits greater predictability for ventures launched by founders with particular backgrounds. While the predicted component of VC judge score strongly predicts funding and innovation outcomes, scientists' scores provide incremental predictive power for innovation outcomes, irrespective of founder characteristics such as age, degree, gender or serial entrepreneurship history.

Turning to startup characteristics in Panel B Table 7, we find that for younger firms, the residual scores of both VC judges and scientist judges have greater predictability

for financing outcomes. In contrast, only the residual scores of scientist judges show a stronger correlation with innovation outcome for younger firms.

# 7. Robustness Checks

### *7.1 Are VC Judges' Evaluations Aligned with Investments?*

One potential concern of the competition setting is that VC judges might evaluate ventures differently in competition than in practice when they have more incentive to allocate time and effort in screening. To address this, we make use of the information collected in a survey of VC judges on the same day that they judged in the competition. Specifically, we test the correlation between the residual component of judge scores and the factors they report as most relevant in the survey (see Appendix C). If judges consistently apply the same investment ideology in both competition and practice, we would expect a large proportion of scores explained (i.e., a smaller residual) by the characteristics they claimed to value. Our regressions include judges' background information, such as education, work experience, overseas study experience, and gender. Additionally, we control for the performance of the VC firm that the judge is affiliated with, including capital raised in the past three years and whether it has had successful IPO exits.

Table C.2 in appendix C presents the results from estimating regression models using the residuals of VC judge scores estimated from different models. Column (1) reports results from the full model, while columns (2) through (5) selectively include or exclude Financials, Innovation, and Team characteristics. Across model

specifications, we find a robust, negative, and significant relationship for Financials and Product & Tech, indicating that VC judges who prioritize these factors in screening indeed have a larger portion of their scores explained (i.e., smaller absolute value of residuals) by the observable venture characteristics. Furthermore, results reveal that more experienced VC judges have a smaller unexplained portion of their scores, indicating their skills in processing noisy information from observable venture characteristics.

### *7.2 Other Measures of Innovation Outcomes*

Beyond patents, we examine other types of innovation outcomes, including professional and technical certificates, software copyrights, and awards for technological achievements (Table E.2 in Appendix E). In general, the results are qualitatively similar to those in Table 3. While both VC and scientist judge scores are positively and significantly related to these innovation outcomes, the coefficients for scientist scores are consistently larger than those for VC scores. This highlights the strong advantage of scientist judges in evaluating the future innovation potentials of the competing ventures.

## 8. External Validity

While VC firms frequently engage external experts when evaluating startups in highly specialized or emerging technology areas, the industry is increasingly hiring partners with in-house technical expertise. Over the past two decades, there has been a

growing number of general partners with PhDs in science, technology, engineering, and math (STEM).

To provide external validation for our competition findings, we analyze a large sample of global VC-backed startups from PitchBook. We identify individual active investors from 2007 to 2015 for whom educational background information is available. We track the exit status of a portfolio company up to March 2022, allowing for at least six years for the development of a venture. Consistent with the literature (Ewens and Marx, 2018), we define a successful exit as either an IPO or a high-value acquisition (at least twice the total investment received). Our sample includes 33,167 distinct portfolio companies affiliated with 22,624 investors.

Figure 3 summarizes the main results. Panel (a) shows that investors with a STEM PhD achieve a 20% success rate, which is significantly higher than the 12% success rate for investors with no STEM degrees or with STEM bachelor's or master's degrees. This superior performance is not purely due to a high level of human capital, as their success rates remain significantly higher than those of investors with non-STEM PhDs (see Figure 3 (b)). Furthermore, this advantage is particularly pronounced in early-stage ventures and technology-intensive sectors (see Figure 3 (c) & (d)).

Despite this clear outperformance, investors with a STEM doctoral degree represented only about 8% of all active VCs during our sample period from 2007 to 2015, suggesting a potential in-house human capital constraint within the industry. These findings provide strong external validation that technology-specific human

capital within the VC firm play an important role, though it is beyond the scope of this paper to disentangle the relative importance of screening versus monitoring.

# 9. Conclusion

This study investigates how VCs and technology-oriented experts evaluate early-stage innovative ventures, highlighting their distinct strengths in predicting different dimensions of venture performance. Using administrative data from a prestigious startup competition in Shanghai, where both VCs and scientists serve as judges, we show that scientists' evaluation can provide significant incremental predictive power for a venture's future innovation output, survival rates, and employment growth, beyond what is captured by the VCs' scores. While scientist scores are not directly aligned with subsequent VC financing in the general market, we find that VC judges incorporate scientist judges' insights into their own investment decisions when they personally served as judges for those ventures. This suggests that VCs face technological-specific human capital constraints, which can be alleviated when scientific expertise becomes accessible.

In line with the technology human capital constraint hypothesis, we find that scientist scores are especially predictive of future VC funding in the AI sector, where technological uncertainty is highest, while VC loses their prediction power. Additionally, for younger startups, scientist scores show stronger predictive power for both subsequent financing and innovation outcomes. Moreover, our survey-based analysis confirms that VC judges' evaluations are aligned with their stated investment

philosophy, with greater reliance on observable venture characteristics among judges who explicitly prioritize such traits. Finally, our results are robust to using alternative measures of innovation outcomes, including certification, software copyrights, and awards for technological achievements.

Consistent with findings derived from analyzing the competition data, external validation using a global sample from Pitchbook reveals that startups backed by VCs with STEM PhDs significantly outperform their peers, even within the high-technology industries. Yet, less than ten percent of portfolio companies in our sample are backed by VCs with STEM PhD background, underscoring the limited in-house technological expertise across the industry. Together, these findings emphasize the importance of technology human capital—whether accessed externally through collaborations or developed internally within VC firms—in improving investment selection and post-investment outcomes.

Our study points to the critical role of technology-proficient human capital in venture capital decision-making and highlights the constraints that arise when such expertise is limited. Our findings contribute to the growing literature on human capital diversity within VC firms, by demonstrating the superior screening ability of domain-specific expertise in predicting real outcomes (innovation, survival, and employment growth). We offer new insights into the mechanisms underlying the financing gap for innovative startups by demonstrating how scientific expertise and venture experience complement one another, revealing how alleviating human capital constraints can enhance early-stage screening and improve capital allocation efficiency. Finally, by

contrasting VC and scientist evaluations within a large-scale venture competition, we provide practical guidance for designing selection mechanisms and intermediary programs that better identify and support transformative entrepreneurial ventures.

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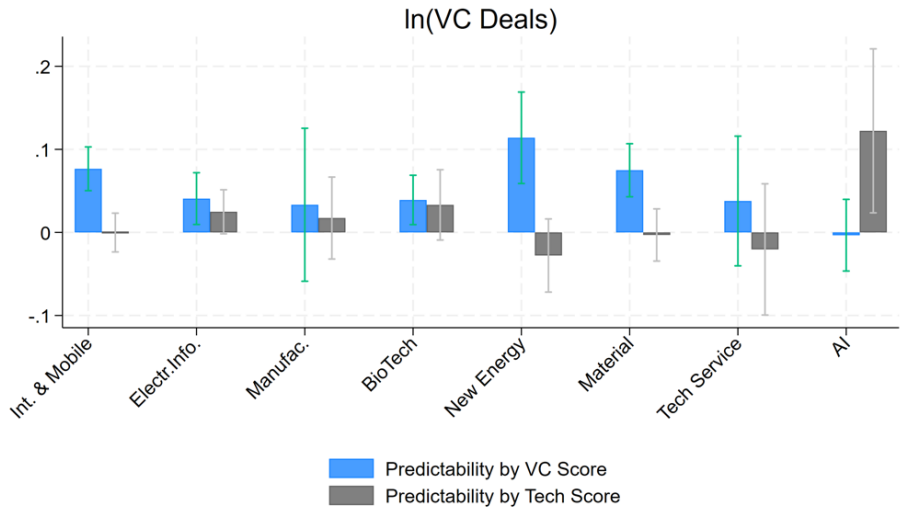
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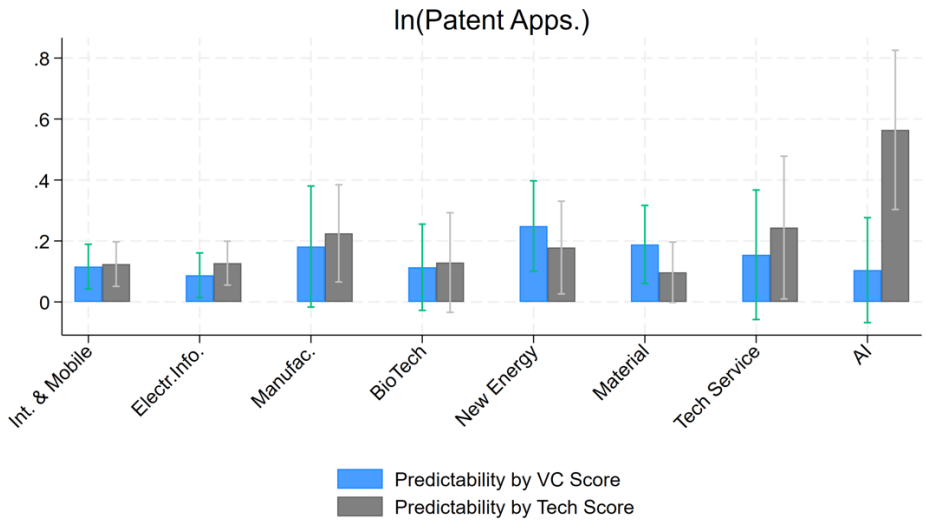
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## Figures and Tables



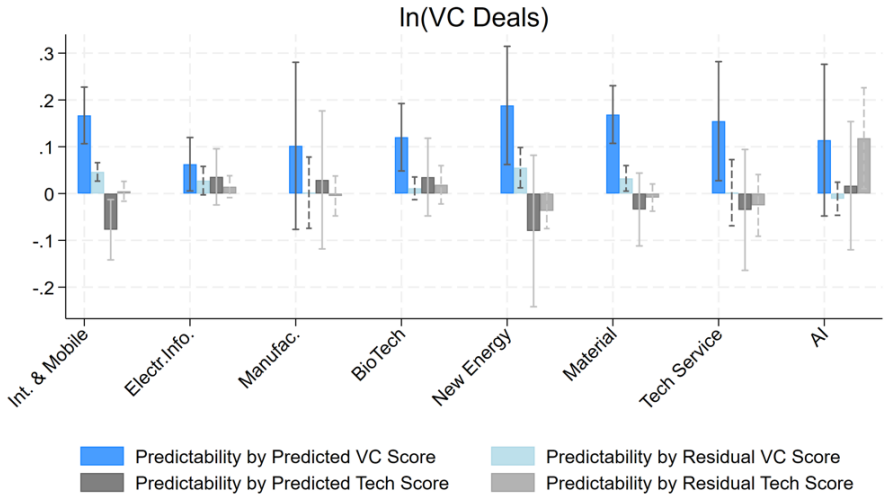

**Panel A: VC Fundraising**



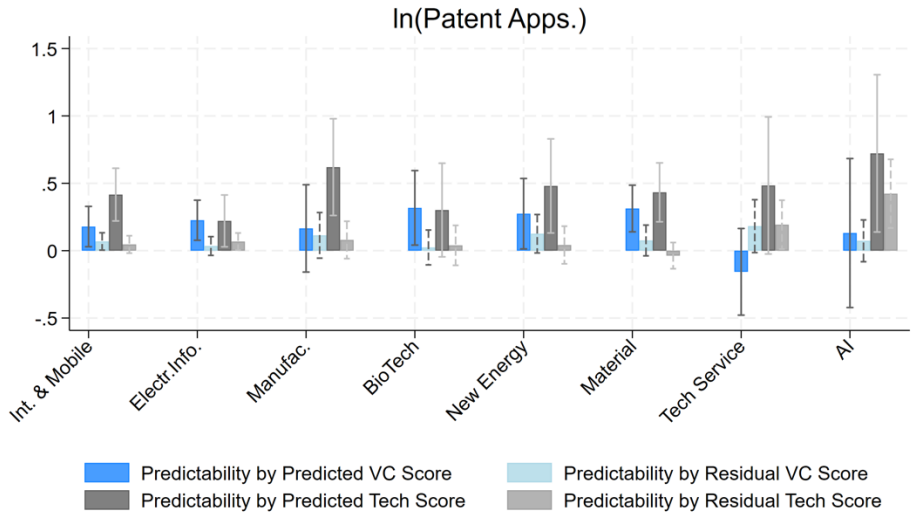

**Panel B: Quantity of Innovation**

### Figure 1. The Predictability of Scores by Industry

This figure plots the coefficients for the predictability of judge evaluations across eight distinct industries, based on regression model (2). The eight industries, classified according to the competition tracks, are: Internet and Mobile (Int. & Mobile), Electronic Information (Electr. Info.), Advanced Manufacturing (Manufac.), Biological Technology (Biotech), New Energy and Environmental (New Energy), New Materials (Material), Services & Technology (Tech Service), and Artificial Intelligence (AI). Each panel corresponds to a different outcome variable. The range plots display the coefficient estimates along with their respective 90% confidence intervals.




**Panel A: VC Funding**

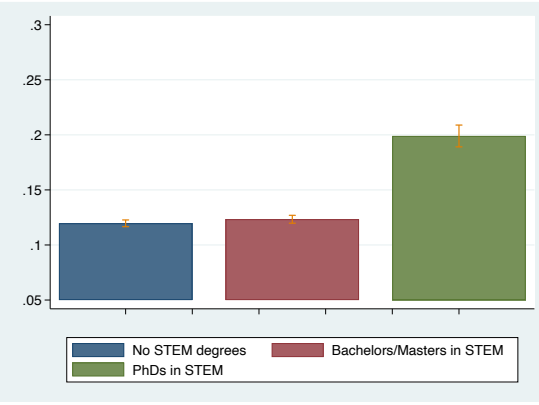



**Panel B: Quantity of Innovation**

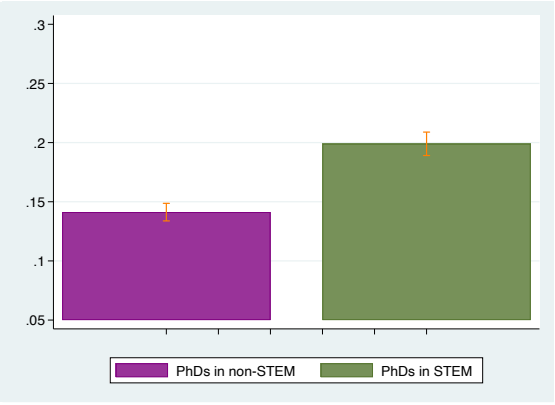
## Figure 2. The Predictability of Decomposed Scores by Industry

The figure displays regression coefficients from model (2) that assess the predictability of evaluation based on the predicted and residual scores of the VC and scientist judge types across eight competition-track industries. The eight industries, classified according to the competition tracks, are: Internet and Mobile (Int. & Mobile), Electronic Information (Electr. Info.), Advanced Manufacturing (Manufac.), Biological Technology (Biotech), New Energy and Environmental (New Energy), New Materials (Material), Services & Technology (Tech Service), and Artificial Intelligence (AI). Each panel corresponds to a different outcome variable. The range plots display the coefficient estimates along with their respective 90% confidence intervals.

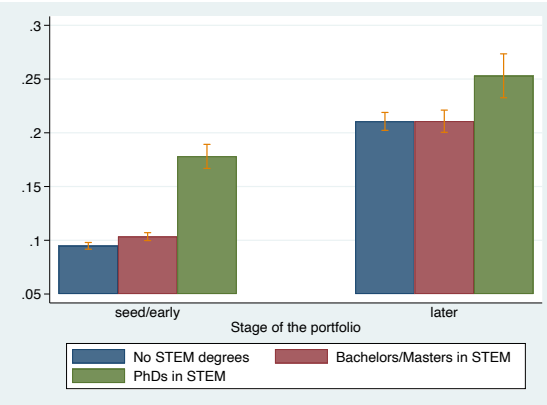
(a) Success rates by STEM degree level




(b) Success rates among PhD investors




(c) Success rates by stages




(d) Success rates by industries

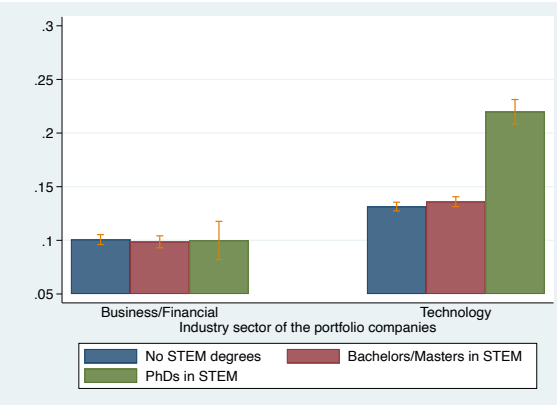



**Figure 3: Success Rates of Portfolio Companies by Investor Education Backgrounds**

This figure plots the success rates of portfolio companies that received VC funding worldwide from 2007 to 2015, based on the educational backgrounds of their affiliated VC investors. We track the exit status of each company up to March 2022, allowing for a minimum of six years of development. A successful exit is defined as either an IPO or a high-value acquisition (at least twice the total investment received). The classification of STEM degrees is based on the U.S. Department of Homeland Security's list, with social sciences (e.g., economics and psychology) excluded. Panel (a) plots the success rates of portfolio companies backed by VCs without STEM degrees, with STEM bachelor's degrees, and with STEM PhD degrees. Panel (b) compares the success rates of portfolio companies backed by VCs with STEM and non-STEM PhD degrees. Panel (c) reports the success rates by the venture's development stage at the time of its first VC funding and by different VC education backgrounds. Panel (d) divides portfolio companies into two industry groups: Business/Financial (B2B, B2C, and Financial Services) and Technology (all other sectors).

## Table 1. Summary Statistics: Application Information

This table summarizes key information from the participant application forms. Panel A breaks down the number of participants by competition year and industry. The eight industries are classified according to the competition organizer's official tracks. Panel B provides summary statistics for the full sample, dividing all variables into six general categories. All the monetary-value variables are in RMB, expressed in the units of 10,000. Detailed definitions and measurement methodology for all variables can be found in Section 3.1.

### Panel A: The Breakdown of Participant Numbers by Competition Year and Industry

| | 2017 Competition | 2018 Competition | 2017 & 2018 |
|---|---|---|---|
| Internet & Mobile | 557 | 348 | 905 |
| Advanced Manufacturing | 400 | 176 | 576 |
| New Materials | 208 | 52 | 260 |
| New Energy & Environmental | 196 | 100 | 296 |
| Biotech | 111 | 222 | 333 |
| Electronic Information | 67 | 565 | 632 |
| Services & Tech | 47 | 73 | 120 |
| Artificial Intelligence | 83 | 0 | 83 |
| Total | 1,669 | 1,536 | 3,205 |

### Panel B: Application Form Variables

| Variable | N | Mean | p1 | p25 | p50 | p75 | p99 |
|---|---|---|---|---|---|---|---|
| Number of Employees | 3205 | 22.4 | 3.0 | 10.0 | 15.0 | 26.0 | 119.0 |
| Age of Firm | 3205 | 4.2 | 0.0 | 2.0 | 3.0 | 5.0 | 18.0 |
| ***Balance Sheet (in 10,000 RMB)*** | | | | | | | |
| Cash | 3205 | 339.3 | 0.0 | 9.4 | 46.0 | 159.3 | 2673.2 |
| Inventory | 3205 | 132.4 | 0.0 | 0.0 | 0.0 | 27.3 | 1045.6 |
| Receivables | 3205 | 156.8 | -14.0 | 0.0 | 13.2 | 105.6 | 1763.0 |
| Intangibles | 3205 | 155.9 | 0.0 | 0.0 | 0.0 | 0.0 | 1496.7 |
| Tangibles | 3205 | 201.1 | 0.0 | 0.0 | 6.0 | 32.4 | 1875.6 |
| Total Assets | 3205 | 985.4 | 0.0 | 45.1 | 162.7 | 558.3 | 5745.0 |
| Payables | 3205 | 157.7 | -27.3 | 0.0 | 4.0 | 54.5 | 1281.6 |
| Short Term Liab. | 3205 | 30.9 | 0.0 | 0.0 | 0.0 | 0.0 | 650.0 |
| Long Term Liab. | 3205 | 101.1 | 0.0 | 0.0 | 0.0 | 0.0 | 101.8 |
| Total Liabilities | 3205 | 289.7 | -21.5 | 0.0 | 5.8 | 68.5 | 1916.0 |
| Book Equity | 3205 | 633.7 | -1203.6 | 1.4 | 104.0 | 500.0 | 6630.5 |
| ***Income Statement (in 10,000 RMB)*** | | | | | | | |
| Revenue | 3205 | 441.6 | 0.0 | 18.4 | 147.8 | 582.7 | 2711.1 |
| Cost of Sales | 3205 | 1194.0 | 0.0 | 0.0 | 41.0 | 273.1 | 2110.6 |
| Sales Tax | 3205 | 8.4 | 0.0 | 0.0 | 0.1 | 1.5 | 38.1 |
| Gross Profit | 3205 | 207.9 | -1002.5 | 0.0 | 24.0 | 184.0 | 1701.4 |
| Operating Expense | 3205 | 182.1 | 0.0 | 0.0 | 0.8 | 34.4 | 950.5 |
| Management Expense | 3205 | 1583.1 | 0.0 | 58.1 | 144.9 | 357.6 | 2513.6 |
| Financial Expense | 3205 | 5.6 | -33.3 | 0.0 | 0.0 | 0.2 | 106.5 |
| R&D Expenses | 3205 | 480.0 | 0.0 | 48.2 | 89.2 | 182.0 | 1598.0 |
| Non-Operating Income (or Expenses) | 3205 | 83.6 | -8.5 | 0.0 | 0.0 | 10.0 | 277.1 |
| Taxes (Total) | 3205 | 30.7 | 0.0 | 0.0 | 1.3 | 14.4 | 305.2 |
| Net Profit | 3205 | -558.0 | -2534.0 | -118.5 | -15.7 | 7.5 | 560.0 |
| Income from Export | 3205 | 2.3 | 0.0 | 0.0 | 0.0 | 0.0 | 73.3 |
| ***Disaggregation of Book Equity (in 10,000 RMB)*** | | | | | | | |
| Book Value | 3205 | 634.0 | -1203.6 | 1.9 | 104.0 | 500.0 | 6630.5 |
| Cumulative Capital | 3205 | 612.7 | 0.0 | 71.4 | 180.4 | 500.0 | 8000.0 |
| Current Gross Profit | 3205 | 207.9 | -1002.5 | 0.0 | 24.0 | 184.0 | 1701.4 |
| Current Expenses | 3205 | 766.2 | -135.8 | 0.0 | 85.1 | 314.1 | 2600.5 |
| Retained Profit | 3205 | 580.0 | -2575.9 | -114.4 | -8.1 | 63.0 | 4955.8 |

## Panel B (Continued): Application Form Variables

| Variable | N | Mean | p1 | p25 | p50 | p75 | p99 |
|---|---|---|---|---|---|---|---|
| ***Technology Stocks*** | | | | | | | |
| Number of Employees with College (or Higher) Degrees | 3205 | 18.525 | 3 | 8 | 13 | 22 | 96 |
| Number of R&D Staff | 3205 | 12.382 | 2 | 6 | 9 | 15 | 64 |
| Number of Patents | 3205 | 1.803 | 0 | 0 | 0 | 2 | 18 |
| Number of Software Copyrights | 3205 | 1.368 | 0 | 0 | 0 | 1 | 16 |
| Number of ICL Designs | 3205 | 0.170 | 0 | 0 | 0 | 0 | 1 |
| Number of Marketed Drugs | 3205 | 0.002 | 0 | 0 | 0 | 0 | 0 |
| Number of Certified Medical Devices | 3205 | 0.010 | 0 | 0 | 0 | 0 | 0 |
| In High-tech Zone | 3205 | 40.75% | 0 | 0 | 0 | 1 | 1 |
| Is Incubator Firm | 3205 | 19.10% | 0 | 0 | 0 | 0 | 1 |
| In Tech Park | 3205 | 0.87% | 0 | 0 | 0 | 0 | 0 |
| In Maker Space | 3205 | 2.81% | 0 | 0 | 0 | 0 | 1 |
| Is High-Tech Enterprise | 3205 | 11.95% | 0 | 0 | 0 | 0 | 1 |
| In Torch Program | 3205 | 0.37% | 0 | 0 | 0 | 0 | 0 |
| ***Human Capital*** | | | | | | | |
| *Entrepreneur* | | | | | | | |
| Age | 3205 | 40.11 | 26 | 35 | 39 | 44 | 66 |
| College Degree | 3205 | 0.08 | 0 | 0 | 0 | 0 | 1 |
| Bachelor Degree | 3205 | 0.39 | 0 | 0 | 0 | 1 | 1 |
| Master Degree | 3205 | 0.41 | 0 | 0 | 0 | 1 | 1 |
| Doctor Degree | 3205 | 0.12 | 0 | 0 | 0 | 0 | 1 |
| Studied Abroad | 3205 | 0.22 | 0 | 0 | 0 | 0 | 1 |
| High-end talent | 3205 | 0.01 | 0 | 0 | 0 | 0 | 1 |
| College Student Tech Enterprise | 3205 | 0.06 | 0 | 0 | 0 | 0 | 1 |
| Number of Firms Founded | 3205 | 0.94 | 0 | 0 | 1 | 1 | 3 |
| *Legal Representative* | | | | | | | |
| Female | 3205 | 0.20 | 0 | 0 | 0 | 0 | 1 |
| Age | 3205 | 42.20 | 26 | 36 | 40 | 47 | 69 |
| College Degree | 3205 | 0.15 | 0 | 0 | 0 | 0 | 1 |
| Bachelor Degree | 3205 | 0.45 | 0 | 0 | 0 | 1 | 1 |
| Master Degree | 3205 | 0.16 | 0 | 0 | 0 | 0 | 1 |
| Doctor Degree | 3205 | 0.11 | 0 | 0 | 0 | 0 | 1 |

## Table 2. Summary Statistics: Post-Competition Performance

This table summarizes the post-competition performance variables for competition participants, which are classified into three distinct categories. Data tracked through January 2024. The first category captures commercialization and financing outcomes, including the number of VC funding deals and the number of trademarks acquired. The second category focuses on innovation activities, including total patent applications (and patent applications filed before the first VC funding date, if applicable), certificates for medical devices and drugs, software copyrights, and awards for scientific achievements. The third category measures real economic performance, including venture survival and employment as of January 2024.

| Variable | N | % Obs. With Non-Zero Values | Mean | p1 | p25 | p50 | p75 | p99 |
|---|---|---|---|---|---|---|---|---|
| Funding Deals | 3205 | 12.0% | 0.29 | 0 | 0 | 0 | 0 | 5 |
| Trademark | 3205 | 42.7% | 6.58 | 0 | 0 | 0 | 4 | 100 |
| Patent Application | 3205 | 45.2% | 7.65 | 0 | 0 | 0 | 7 | 97 |
| Patent Application (Before first VC Funding) | 3205 | 41.8% | 5.28 | 0 | 0 | 0 | 5 | 61 |
| Certificate | 3205 | 47.3% | 2.56 | 0 | 0 | 0 | 3 | 28 |
| Software Copyright | 3205 | 54.3% | 8.12 | 0 | 0 | 1 | 13 | 50 |
| Awards | 3205 | 43.5% | 1.28 | 0 | 0 | 0 | 2 | 7 |
| Survival | 3205 | 13.70% | 0.86 | 0 | 1 | 1 | 1 | 1 |
| Employment | 3205 | 30.98% | 17.28 | 0 | 0 | 3 | 15 | 213 |

## Table 3. Judge Score Prediction on Long-Run Real Performance

This table presents regression coefficients from model (2), examining the relationship between judge evaluations and long run venture performance. Panels A through C use different outcome variables. In panel A, columns (1)-(4) use a binary indicator for positive number of patent applications (the extensive margin), while columns (5)-(8) use the logarithm of one plus the patent application count, representing the intensive margin. In Panel B, columns (1) to (4) examine the logarithm of one plus the number of high citation patents, classified as the patents with above-median citation counts, with at least one citation in a year within the patent class. Columns (5) to (8) examine the logarithm of average patent citations. Panel C uses Survival (a dummy indicator equal to 1 if the startup company is alive) and the logarithm of the number of employees by the Jan of 2024. All specifications include three sets of fixed effects: competition year, VC judge panel, and industry. Standard errors are clustered at the competition and industry levels, with t-statistics for the coefficients are reported in the parentheses. * p < .10; ** p < .05; *** p < .01.

### Panel A: Patent Application Number

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *1(Patent App.>0)* | | | | *ln(1+Patent App.)* | | | |
| VC Judge Score | 0.040*** | 0.044*** | | | 0.120*** | 0.131*** | | |
| | (4.12) | (4.50) | | | (4.35) | (4.76) | | |
| Scientist Judge Score | | 0.054*** | | | | 0.159*** | | |
| | | (5.51) | | | | (6.33) | | |
| Predicted VC Judge Score | | | 0.084*** | 0.041** | | | 0.343*** | 0.177*** |
| | | | (5.35) | (2.31) | | | (7.87) | (3.62) |
| Residual VC Judge Score | | | 0.021** | 0.029*** | | | 0.040 | 0.064*** |
| | | | (2.36) | (3.24) | | | (1.62) | (2.61) |
| Predicted Scientist Judge Score | | | | 0.145*** | | | | 0.510*** |
| | | | | (6.51) | | | | (8.27) |
| Residual Scientist Judge Score | | | | 0.023** | | | | 0.039* |
| | | | | (2.54) | | | | (1.73) |
| Winner of Competition | 0.127*** | 0.055** | 0.112*** | 0.047* | 0.445*** | 0.232*** | 0.375*** | 0.193** |
| | (5.43) | (2.03) | (4.70) | (1.72) | (6.66) | (3.04) | (5.61) | (2.57) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 3205 | 3205 | 3203 | 3203 |
| R-sq. | 0.1205 | 0.1283 | 0.1250 | 0.1368 | 0.1532 | 0.1623 | 0.1667 | 0.1850 |

### Panel B: Patent Quality

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *ln(1+High-Citation Patents)* | | | | *ln(1+Citations)* | | | |
| VC Judge Score | 0.193*** | 0.205*** | | | 0.008 | 0.012 | | |
| | (3.52) | (3.72) | | | (0.51) | (0.78) | | |
| Scientist Judge Score | | 0.178*** | | | | 0.044*** | | |
| | | (3.95) | | | | (2.61) | | |
| Predicted VC Judge Score | | | 0.830*** | 0.700*** | | | 0.061*** | 0.065*** |
| | | | (7.39) | (5.64) | | | (2.92) | (2.72) |
| Residual VC Judge Score | | | -0.007 | 0.011 | | | -0.011 | -0.007 |
| | | | (0.15) | (0.24) | | | (-0.75) | (-0.45) |
| Predicted Scientist Judge Score | | | | 0.393*** | | | | 0.019 |
| | | | | (2.98) | | | | (0.52) |
| Residual Scientist Judge Score | | | | 0.022 | | | | 0.034** |
| | | | | (0.56) | | | | (2.24) |
| Winner of Competition | 0.614*** | 0.376** | 0.423*** | 0.292* | -0.007 | -0.063 | -0.021 | -0.064 |
| | (4.55) | (2.40) | (3.20) | (1.92) | (-0.19) | (-1.55) | (-0.61) | (-1.59) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 1448 | 1448 | 1448 | 1448 |
| R-sq. | 0.0678 | 0.0711 | 0.0979 | 0.1011 | 0.0173 | 0.0218 | 0.0232 | 0.0265 |

### Panel C: Survival & Employment

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *Survival* | | | | *ln(Employment)* | | | |
| VC Judge Score | 0.013* | 0.015* | | | 0.220*** | 0.234*** | | |
| | (1.69) | (1.88) | | | (6.75) | (7.18) | | |
| Scientist Judge Score | | 0.026*** | | | | 0.197*** | | |
| | | (3.18) | | | | (6.91) | | |
| Predicted VC Judge Score | | | 0.012 | -0.013 | | | 0.544*** | 0.326*** |
| | | | (1.05) | (-1.02) | | | (10.90) | (5.67) |
| Residual VC Judge Score | | | 0.011 | 0.015** | | | 0.095*** | 0.125*** |
| | | | (1.49) | (2.01) | | | (3.27) | (4.33) |
| Predicted Scientist Judge Score | | | | 0.081*** | | | | 0.658*** |
| | | | | (4.50) | | | | (9.33) |
| Residual Scientist Judge Score | | | | 0.012 | | | | 0.034 |
| | | | | (1.60) | | | | (1.35) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Winner of Competition | 0.040** | 0.005 | 0.038** | 0.003 | 0.425*** | 0.162* | 0.319*** | 0.104 |
| | (2.32) | (0.27) | (2.22) | (0.15) | (5.56) | (1.87) | (4.21) | (1.23) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 3205 | 3205 | 3203 | 3203 |
| R-sq. | 0.0325 | 0.0327 | 0.0335 | 0.0339 | 0.0543 | 0.0544 | 0.0649 | 0.0649 |

## Table 4. Judge Score Prediction on Future Fundraising and Commercialization

This table presents the coefficients from Model (2), examining the relationship between judge evaluations and subsequent fundraising and commercialization outcomes. Panels A and B feature different outcome variables. For Panel A and Panel B, columns (1) to (4) use a binary indicator for the positive number of deals or trademarks, respectively (the extensive margin), while columns (5) to (8) apply a logarithmic transformation of one plus the count, representing the intensive margin. All specifications include three sets of fixed effects: competition year, VC judge panel, and industry. Standard errors are clustered at the competition and industry levels, with t-statistics for the coefficients provided in the parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

**Panel A: VC Deals**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *1(Deals>0)* | | | | *ln(1+Deals)* | | | |
| VC Judge Score | 0.045*** | 0.046*** | | | 0.057*** | 0.058*** | | |
| | (6.70) | (6.84) | | | (6.11) | (6.23) | | |
| Scientist Judge Score | | 0.006 | | | | 0.009 | | |
| | | (1.00) | | | | (1.16) | | |
| Predicted VC Judge Score | | | 0.101*** | 0.109*** | | | 0.132*** | 0.143*** |
| | | | (8.28) | (7.56) | | | (7.75) | (7.07) |
| Residual VC Judge Score | | | 0.023*** | 0.022*** | | | 0.027*** | 0.026*** |
| | | | (3.78) | (3.73) | | | (3.39) | (3.33) |
| Predicted Scientist Judge Score | | | | -0.021 | | | | -0.028 |
| | | | | (-1.28) | | | | (-1.31) |
| Residual Scientist Judge Score | | | | 0.002 | | | | 0.003 |
| | | | | (0.30) | | | | (0.39) |
| Winner of Competition | 0.065*** | 0.056*** | 0.046** | 0.049** | 0.075*** | 0.063** | 0.051** | 0.055** |
| | (3.62) | (2.84) | (2.55) | (2.53) | (3.43) | (2.55) | (2.31) | (2.24) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 3205 | 3205 | 3203 | 3203 |
| R-sq | 0.0756 | 0.0759 | 0.0921 | 0.0927 | 0.0752 | 0.0756 | 0.0954 | 0.0961 |

**Panel B: Trademarks**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *1(Number>0)* | | | | *ln(1+Number)* | | | |
| VC Judge Score | 0.033*** | 0.032*** | | | 0.133*** | 0.134*** | | |
| | (3.12) | (3.06) | | | (4.63) | (4.67) | | |
| Scientist Judge Score | | -0.008 | | | | 0.017 | | |
| | | (-0.78) | | | | (0.64) | | |
| Predicted VC Judge Score | | | 0.051*** | 0.051*** | | | 0.309*** | 0.315*** |
| | | | (3.19) | (2.82) | | | (6.89) | (6.15) |
| Residual VC Judge Score | | | 0.022** | 0.021** | | | 0.063** | 0.061** |
| | | | (2.25) | (2.11) | | | (2.39) | (2.34) |
| Predicted Scientist Judge Score | | | | -0.009 | | | | -0.022 |
| | | | | (-0.38) | | | | (-0.35) |
| Residual Scientist Judge Score | | | | -0.011 | | | | -0.006 |
| | | | | (-1.11) | | | | (-0.24) |
| Winner of Competition | 0.061** | 0.072** | 0.053** | 0.068** | 0.203*** | 0.180** | 0.145** | 0.157** |
| | (2.48) | (2.53) | (2.14) | (2.40) | (3.09) | (2.39) | (2.18) | (2.09) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 3205 | 3205 | 3203 | 3203 |
| R-sq. | 0.0325 | 0.0327 | 0.0335 | 0.0339 | 0.0543 | 0.0544 | 0.0649 | 0.0649 |

## Table 5. Evaluation and VC Judges' Investments in Competing Ventures

This table presents regression coefficients from model (3), which examines the relationship between evaluations and subsequent investment decisions by VC investors who served as judges. The regression sample is constructed at the startup-investor level and considers all the potential pairs of start-ups and VC investors who acted as judges. The outcome variable is normalized investment, defined as an indicator of whether the investor made an investment in the startup (normalized by dividing by the unconditional mean). All specifications include three sets of fixed effects: competition year, VC judge panel, and industry, plus competition year-VC firm level fixed effects. Standard errors are clustered at the competition and industry levels, with t-statistics for the coefficients provided in the parentheses. * p < .10; ** p < .05; *** p < .01.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Dep. Var.= Normalized Investment** | | | | |
| VC Judge Score | 0.475*** | 0.474*** | | |
| | (3.42) | (3.41) | | |
| Scientist Judge Score | | -0.017 | | |
| | | (-0.12) | | |
| Predicted VC Judge Score | | | 1.076*** | 1.337*** |
| | | | (5.03) | (5.51) |
| Residual VC Judge Score | | | 0.230* | 0.202 |
| | | | (1.78) | (1.55) |
| Predicted Scientist Judge Score | | | | -0.737** |
| | | | | (-2.25) |
| Residual Scientist Judge Score | | | | 0.025 |
| | | | | (0.19) |
| Winner of Competition | 1.269*** | 1.292*** | 1.071*** | 1.235*** |
| | (3.88) | (3.39) | (3.23) | (3.24) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes |
| Fixed Effects (Competition Year-VC Firm) | Yes | Yes | Yes | Yes |
| N | 334324 | 334324 | 334124 | 334124 |
| R-sq. | 0.0018 | 0.0018 | 0.0019 | 0.0019 |

## Table 6. When do VC Judges Invest in the Competing Ventures?

This table presents the coefficients from Model (4), examining whether the relationship between evaluations and subsequent investment decisions by VC judges differs based on whether the judge was on the startup's evaluation panel. The dataset is constructed at the startup-investor level, includes all potential pairs of start-ups and VC investors who acted as judges. The dependent variable is normalized investment, defined as an indicator of investment activity normalized by its unconditional mean. All specifications include fixed effects for competition year, VC judge panel, and industry, as well as competition year-VC firm level fixed effects. Standard errors are clustered at the competition and industry levels, with t-statistics reported in parentheses. * p < .10; ** p < .05; *** p < .01.

| | (1) | (2) |
|---|---|---|
| **Dep. Var.= Normalized Investment** | | |
| Predicted VC Judge Score*Judged | 2.153*** | 6.928*** |
| | (2.92) | (5.04) |
| Predicted VC Judge Score*Not Judged | 1.044*** | 1.172*** |
| | (4.86) | (4.77) |
| Residual VC Judge Score*Judged | 0.684 | 0.619 |
| | (0.94) | (0.85) |
| Residual VC Judge Score*Not Judged | 0.216* | 0.189 |
| | (1.65) | (1.43) |
| Predicted Scientist Judge Score *Judged | | -5.853*** |
| | | (-4.22) |
| Predicted Scientist Judge Score *Not Judged | | -0.585* |
| | | (-1.78) |
| Residual Scientist Judge Score *Judged | | 1.901*** |
| | | (2.58) |
| Residual Scientist Judge Score *Not Judged | | -0.030 |
| | | (-0.22) |
| Winner of Competition * Judged | 4.724*** | 3.910*** |
| | (3.33) | (2.62) |
| Winner of Competition * Not Judged | 0.964*** | 1.157*** |
| | (2.89) | (3.02) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes |
| Fixed Effects (Competition Year-VC Firm) | Yes | Yes |
| N | 334124 | 334124 |
| R-sq. | 0.0019 | 0.0020 |

## Table 7. Heterogeneous Effects

This table examines how founder background and startups characteristics influence the predictive power of judge scores. The heterogeneous effects of scores' predictability are captured by the coefficients on the interaction terms between the residual component of VC and scientist judge scores and the respective characteristics. Only residual components of the scores are analyzed because the predicted component already accounts for the non-linear relationship between the scores and the characteristics as specified in Equation (1). In Panel A, we consider four characteristics of the founder: age (log), highest degree (1=high school, 2=Bachelor Degree, 3=master degree, 4=PhD), serial entrepreneur (indicator variable), and female (indicator variable). In Panel B, we consider three characteristics of the venture: firm age (log), whether the firm has negative profit (indicator variable), and asset's tangibility. Standard errors are clustered at the competition and industry levels, with t-statistics for the coefficients provided in parentheses. * p < .10; ** p < .05; *** p < .01.

**Panel A. Founder's Characteristics**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *1(Deals>0)* | *ln(1+Deals)* | *1(Pat. App.>0)* | *ln(1+Pat. App.)* |
| Predicted VC Judge Score | 0.112*** | 0.147*** | 0.039** | 0.176*** |
| | (7.69) | (7.16) | (2.18) | (3.54) |
| Residual VC Judge Score | 0.185* | 0.195 | -0.115 | -0.192 |
| | (1.94) | (1.59) | (-0.75) | (-0.46) |
| Residual VC Judge Score*lnage | -0.046* | -0.048 | 0.041 | 0.067 |
| | (-1.81) | (-1.45) | (0.97) | (0.57) |
| Residual VC Judge Score*Degree | 0.009 | 0.013 | -0.001 | 0.014 |
| | (1.15) | (1.17) | (-0.08) | (0.45) |
| Residual VC Judge Score*Serial | -0.026 | -0.038 | -0.010 | -0.020 |
| | (-1.40) | (-1.44) | (-0.47) | (-0.34) |
| Residual VC Judge Score*Female | 0.000 | 0.000 | -0.017 | -0.013 |
| | (0.00) | (0.01) | (-0.58) | (-0.15) |
| Predicted Scientist Judge Score | -0.022 | -0.029 | 0.146*** | 0.512*** |
| | (-1.33) | (-1.38) | (6.47) | (8.25) |
| Residual Scientist Judge Score | -0.077 | -0.076 | 0.162 | 0.225 |
| | (-0.80) | (-0.71) | (1.07) | (0.58) |
| Residual Scientist Judge Score*lnage | 0.021 | 0.020 | -0.041 | -0.059 |
| | (0.82) | (0.70) | (-1.00) | (-0.57) |
| Residual Scientist Judge Score*Degree | 0.002 | 0.005 | 0.005 | 0.020 |
| | (0.23) | (0.50) | (0.47) | (0.66) |
| Residual Scientist Judge Score*Serial | -0.015 | -0.012 | -0.007 | -0.019 |
| | (-0.82) | (-0.61) | (-0.31) | (-0.34) |
| Residual Scientist Judge Score*Female | 0.012 | 0.009 | 0.026 | 0.034 |
| | (0.70) | (0.49) | (0.96) | (0.48) |
| Winner of Competition | 0.043** | 0.046* | 0.047* | 0.185** |
| | (2.16) | (1.84) | (1.68) | (2.39) |
| N | 3182 | 3182 | 3182 | 3182 |
| R-sq. | 0.0956 | 0.0989 | 0.1376 | 0.1855 |

## Panel B. Venture Characteristics

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *1(Deals>0)* | *ln(1+Deals)* | *1(Pat. App.>0)* | *ln(1+Pat. App.)* |
| Predicted VC Judge Score | 0.106*** | 0.140*** | 0.039** | 0.173*** |
| | (7.39) | (6.93) | (2.21) | (3.54) |
| Residual VC Judge Score | 0.063*** | 0.091*** | 0.087*** | 0.171** |
| | (2.71) | (2.83) | (3.07) | (2.22) |
| Residual VC Judge Score*lnFirmAge | -0.043** | -0.063*** | -0.036 | -0.122* |
| | (-2.30) | (-2.62) | (-1.42) | (-1.80) |
| Residual VC Judge Score*Has Negative Profit | 0.005 | 0.004 | -0.023 | 0.075 |
| | (0.36) | (0.20) | (-0.89) | (1.09) |
| Residual VC Judge Score*Tangibility | 0.026 | 0.033 | -0.051 | -0.068 |
| | (0.62) | (0.53) | (-1.01) | (-0.47) |
| Predicted Scientist Judge Score | -0.024 | -0.032 | 0.142*** | 0.500*** |
| | (-1.47) | (-1.49) | (6.36) | (8.10) |
| Residual Scientist Judge Score | 0.073*** | 0.078*** | 0.075** | 0.231*** |
| | (3.12) | (2.74) | (2.18) | (2.66) |
| Residual Scientist Judge Score*lnFirmAge | -0.058*** | -0.058*** | -0.053* | -0.173** |
| | (-2.93) | (-2.65) | (-1.78) | (-2.29) |
| Residual Scientist Judge Score*Has Negative Profit | 0.009 | 0.001 | 0.015 | 0.015 |
| | (0.50) | (0.05) | (0.55) | (0.22) |
| Residual Scientist Judge Score*Tangibility | -0.067* | -0.072* | 0.006 | -0.003 |
| | (-1.67) | (-1.70) | (0.11) | (-0.02) |
| Winner of Competition | 0.063*** | 0.071*** | 0.059** | 0.226*** |
| | (3.13) | (2.82) | (2.12) | (2.96) |
| N | 3203 | 3203 | 3203 | 3203 |
| R-sq. | 0.0991 | 0.1020 | 0.1393 | 0.1877 |

# Online Appendix

## Appendix A. Survey Questions

### A1. Outline of the application form submitted by the competing ventures

1. **Basic information of the venture**
   - Industry, whether it is located in a national incubator, whether it is located in a national high-tech zone, registration details (address, capital, employees, legal representative), list of rewards/supports acquired, whether the primary shareholder is a public company.

   - Core technology (patents, software copyrights, drug approval, medical device registration certificates, integrated circuit layout, keywords, summary, whether it is from technology transfer)

   - Historical financial statements
2. **Information of the shareholders**
   - names/titles, capital contributed, shares owned.

3. **Core team members**
   - recent photo of all core members together, resume of each member.

4. **Business plan of the project**
   - technology description, main product/service, market analysis, supplier/customer analysis, competition analysis, business model, expansion plans, risk analysis, management.

5. **Project development objective**
   - Input and expenses, product growth objectives in the next two years, business development projection in the next three year.

6. **Entrepreneurial services needed**
   - Past experience of equity/debt financing, whether currently look for support in equity/debt financing, consulting services, or technology transfer.

**A2. Survey questions for VC judges**

1. **In which years did you serve as a judge for the Pudong Innovation & Entrepreneurship Competition?**

2. **Have you or your investment institution invested in any projects that participated in past competitions?**

   If yes, please provide the following information: project name or founder's name, whether you serve as a judge for this project.

3. **What factors do you value most when evaluating investment projects? (Choose up to three):**
   - Team
   - Financial situation
   - Technology / Product
   - Intellectual property ownership
   - Market prospects
   - Business model
   - Other (please specify)

4. **Which industries are you interested in investing in?**
5. **What type of investment institution do you represent?**
   a. Angel investment fund
   b. Venture capital fund
   c. Private equity fund
   d. Other (please specify)

6. **What is the approximate total fund amount raised by you or your institution in the past three years?**

7. **How many years of investment experience do you personally have?**

8. **How many of the companies you have invested in have successfully gone public?**

9. **What is your highest level of education?**

10. **Have you obtained any degree overseas (including Hong Kong, Macao, Taiwan)?**
    If yes, in which country did you obtain your degree? _____

11. **Regarding today's projects you evaluated, do you or your investment institution have investment intentions?**

If yes, please provide the following information:

- Project name or founder's name): _____
    - What are the reasons this project attracts you? (Multiple choices allowed)
        - Team
        - Financial situation
        - Technology / Product
        - Intellectual property ownership
        - Market prospects
        - Business model
        - Other (please specify)

## Appendix B. Judge Evaluations and Start-up Characteristics

We estimate Equation (1) with a focus on book equity characteristics. The estimation results are presented in Table B.1, with each panel corresponding to a different dependent variable: the VC judge score, the scientist judge score, and the total score. All regressions control for competition year, VC judge panel, and industry fixed effects.

We begin with a baseline model in column (1), where we regress the VC judge score on the cumulative equity raised by the venture at the time of application. In column (2), the model is expanded to include retained earnings, current gross profits (or losses), and current expenses (both positive and negative). Column (3) combines all book equity characteristics into a single regression. Columns (4) through (8) progressively introduce additional venture features as regressors, including other financial metrics, innovation activities (at the time of the competition), team characteristics, and other relevant control variables.

The results suggest that higher equity raised is associated with higher VC scores. VC judges appear to favour ventures with both higher current gross profits and losses, indicating their openness to ventures at different financial stages. They also tend to give higher scores when expenses are greater. While VC judges do value positive retained earnings, the association is relatively weak. In contrast, Panel B of Table B.1 shows that although scientist judges also favour ventures with higher raised equity, they exhibit a distinct pattern: they place value on current gross profits, but retained earnings do not influence their scores. Additionally, scientist judges respond positively only to

negative current expenses, likely because larger expenses may signal negative cashflow in the near future.

When higher-order polynomials are incorporated into the models (columns (9) and (10)), we observe a further shift. The previously weak link between positive retained earnings and VC scores diminishes, suggesting a more complex relationship. Similarly, scientist judges become less sensitive to current gross profit when it is negative (i.e., gross loss), indicating that this factor may play a more nuanced role in their evaluations. In Panel C of Table B.1, we analyse the total score (the weighted average of VC and scientist judge scores), the characteristics that are significant for both VC and scientist judges remain significant for the total score, emphasizing their consistent importance across both perspectives.

Our analysis extends beyond book equity characteristics, revealing that the differing sensitivities of VC and scientist judges' scores apply to a broader range of firm attributes. Figure B.2 visually illustrates this difference. We group various firm characteristics into six categories: Book Equity, Balance Sheet, Income Statement, Funding, Innovation, and Team. For each characteristic, we plot the estimated coefficients from Equation (1) for both VC and scientist judges. The blue dots represent pairs of these coefficients, with each dot showing the scientist judges' coefficient plotted against the corresponding coefficient for the VC judges. The red lines depict the fitted linear relationships between the estimated coefficients of the two judge groups. Across all six categories of commonly observable venture characteristics from the

application package, we find that VC judges generally exhibit lower sensitivity to venture characteristics compared to the scientist judges.

Furthermore, our analysis reveals that VC and scientist judges not only prioritize different venture characteristics, but also process observable information in distinct ways. The relatively low correlation coefficient of 0.5 between the predicted scores of VC judges and scientist judges (i.e., $\hat{f}^{\mathrm{VC}}(\mathrm{X_i})$ and $\hat{f}^{Tech}(\mathrm{X_i})$) suggests a substantial difference in how they utilize and interpret the same information, indicating the use of contrasting evaluation techniques. To explore this further, we alter the functional form f(.) in regression (1) while using the same venture characteristics. In the last two columns of Table B.1, we introduce higher-order terms for all venture characteristics. We extend this analysis by employing polynomials up to the $10^{\text{th}}$ power and plot the adjusted R-squares (goodness-of-fit) in Figure B.3. Our findings reveal a distinct pattern: the adjusted R-squares for VC, scientist, and total scores gradually increase as we move from a model that includes only book equity information to one that incorporates additional financial variables and, ultimately, all available venture characteristics. For VC scores, the model fit continues to improve with increasing polynomial orders, stabilizing around the 5th power. This suggests that complex interactions and non-linear relationships play a significant role in their evaluations. In contrast, R-squares for scientist scores show minimal change, even when higher-order polynomials are included. This indicates that linear models with lower-order interactions are sufficient to capture the relationship between observables and scientist judge evaluations. Moreover, Figure B.3 demonstrates that the R-square of the

weighted average consistently surpasses those of individual scores. Further analysis with higher-order polynomials and varying weights re-affirms this trend.

Finally, regarding private information, we find a near-zero correlation coefficient between the residuals from the VC and scientist score decompositions (i.e., $\hat{\varepsilon}_{i,t,p}^{VC}$ and $\hat{\varepsilon}_{i,t,p}^{Tech}$), which indicates that VC and scientist judges likely possess independent private information sets. Moreover, we observe that VC judges rely more heavily on private information than scientists when evaluating the early-stage startups in the competition. Comparing the adjusted R-squares in Panels A and B of Table B.1 (and in Figure B.3) reveals a striking difference: the average adjusted R-squared for scientist judge scores is, on average, twice as large as that for VC scores. This indicates that observable venture characteristics have significantly more explanatory power for scientist judge evaluations compared to their VC counterparts. This finding aligns with the competition's structure, where scientist judges primarily rely on application materials, whereas VC judges evaluate applications by combining both application materials and pitch performance. The reliance on private information, gleaned from pitch performances and other sources, likely explains the larger proportion of unexplained variance in their scores. This finding also reflects industry practice, as VC judges often incorporate unquantifiable factors and intuition, alongside objective data, when assessing ventures.

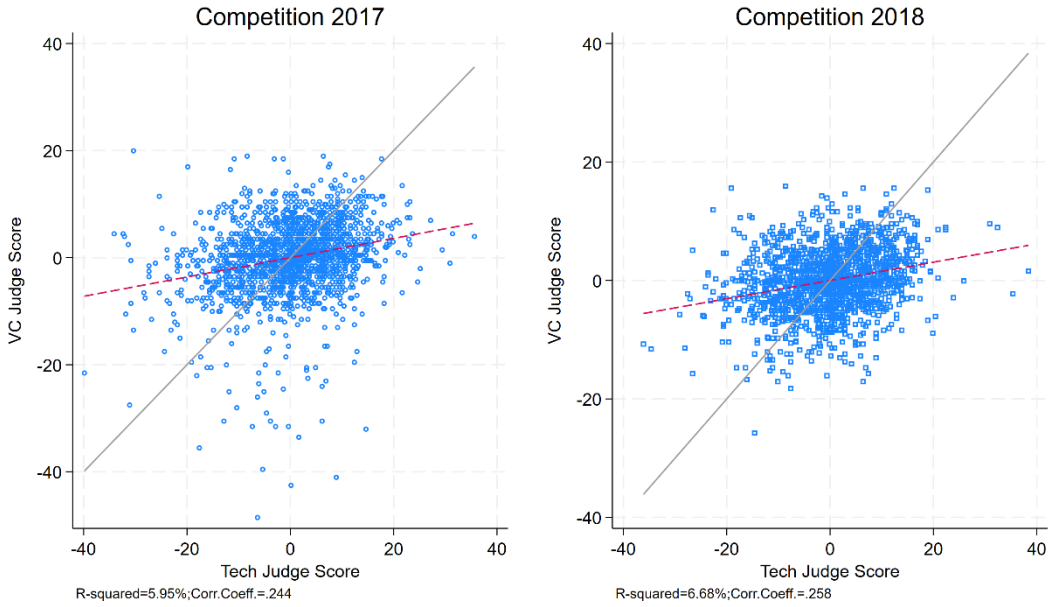



**Figure B.1. The Correlation Between Scores from VC and Scientist Judges**

The figures illustrate the correlation between the VC judge scores (raw) and scientist judge scores (raw) for the 2017 and 2018 competitions. Each dot in the scatter plot represents an individual venture. The solid line corresponds to the 45-degree reference line, while the dashed line represents the linear fit of the data. Below each figure, the R-squared value from the OLS regression of VC scores on scientist scores, along with the correlation coefficient between the two scores, is reported.

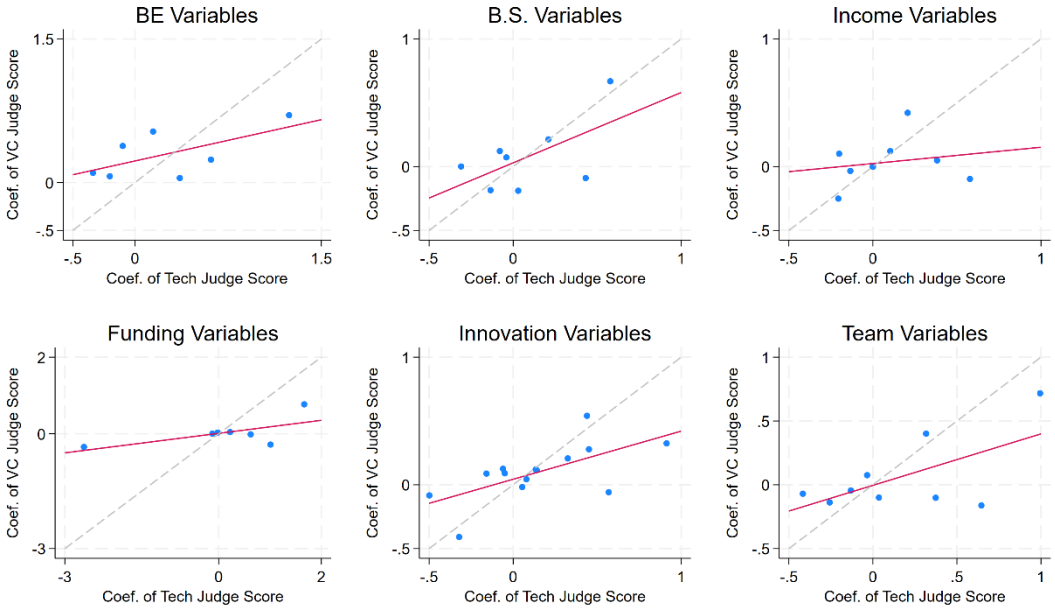
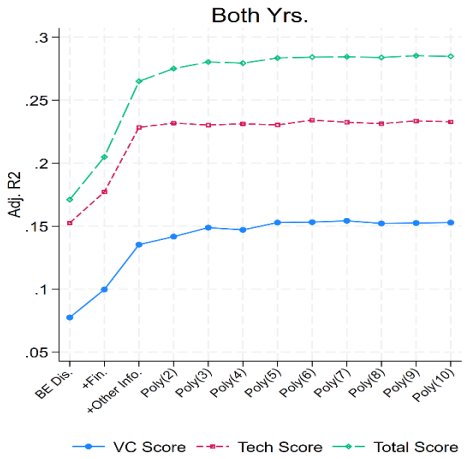
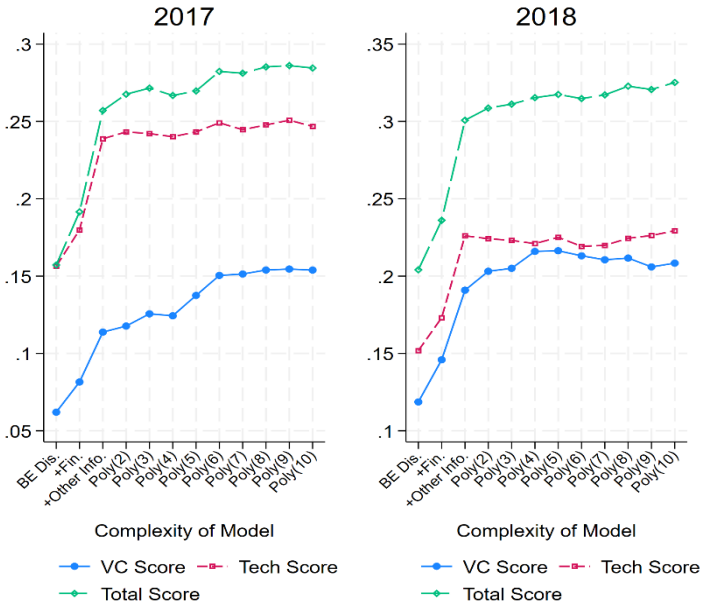



**Figure B.2. Regressions Coefficients Using Different Scores as Dependent Variables**

This figure illustrates the differences in how VC judges and scientist judges weight various firm characteristics when assigning scores. The plotted points represent the first-order regression coefficients for the VC judge score and the Scientist judge score on each characteristic, using the decomposition regression model (1) with a polynomial order of 10. For each characteristic, the two coefficients are plotted against one another. The characteristic variables are categorized into: book equity ("BE" variables), balance sheet ("B.S." variables), income statement (Income variables), project funding (Funding variables), innovation performance, and entrepreneurship team at the application (refer to Section 3 and Table 1 for full details). Each plot positions the VC coefficient against the scientist coefficient for the same characteristic.




**Panel A: Full Sample**




**Panel B: Sub-sample by Competition Year**

## Figure B.3. Fitness of Regression Models for Explaining Scores

The figure illustrates how the adjusted R-squared of the score decomposition model (Equation (1)) varies as the regression's functional form increases in complexity across 12 specifications. The complexity is added in three phases: first, by including only Book Equity disaggregated variables; second, by adding other financial variables (balance sheet and income statement); and third, by progressively increasing the polynomial order for all venture characteristics. Panel A shows the results for the full sample, while Panel B provides the subsample results by competition year. In each panel, three lines depict the results for the three different dependent variables: VC judge score, scientist judge score, and total score.

## Table B.1. The Relevance of Accounting Information for Judge Scoring

This table presents the results from estimating the judge score decomposition Equation (1), which regresses judge scores on observable venture characteristics. Each panel corresponds to a different dependent variable: VC judge score, scientist judge score, and total score (as the weighted average). For brevity, only the first-order coefficients for the disaggregated book equity variables (represent key accounting information) are shown. The specifications differ in the included regressors and the polynomial order, which are indicated at the bottom of each panel. All specifications include three sets of fixed effects: competition year, VC judge panel, and industry. The table reports both the R-squared and the within-group adjusted R-squared values for the fixed effects. Standard errors are clustered at the competition and industry levels, with t-statistics for the coefficients provided in the parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01.

**Panel A: Dependent Variable=VC Judge Score**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Cumulative Equity Raised | 0.813*** | | 0.453*** | 0.218 | 0.360*** | 0.449*** | 0.499*** | 0.254* | 0.236* | 0.172 |
| | (7.16) | | (3.48) | (1.54) | (2.72) | (3.46) | (3.74) | (1.81) | (1.66) | (1.20) |
| Positive Retained Earnings | | 0.473*** | 0.338** | 0.054 | 0.088 | 0.322** | 0.399** | 0.098 | 0.141 | 0.165 |
| | | (2.95) | (2.05) | (0.31) | (0.53) | (1.98) | (2.36) | (0.57) | (0.79) | (0.92) |
| Negative Retained Earnings | | 0.291* | 0.051 | 0.049 | -0.096 | 0.018 | 0.119 | 0.059 | 0.081 | 0.107 |
| | | (1.95) | (0.31) | (0.30) | (-0.58) | (0.11) | (0.72) | (0.36) | (0.48) | (0.63) |
| Current Gross Profit | | 0.503*** | 0.451*** | 0.552** | 0.560*** | 0.614*** | 0.674*** | 0.643*** | 0.560** | 0.484** |
| | | (3.21) | (2.87) | (2.43) | (3.41) | (3.93) | (4.00) | (2.87) | (2.47) | (2.12) |
| Current Gross Loss | | 0.861*** | 0.792*** | 0.645*** | 0.692*** | 0.750*** | 0.707*** | 0.525*** | 0.596*** | 0.539*** |
| | | (6.15) | (5.61) | (4.09) | (4.83) | (5.38) | (4.92) | (3.36) | (3.77) | (3.37) |
| Negative Current Expenses | | 0.256** | 0.241* | 0.062 | 0.140 | 0.201 | 0.251** | 0.052 | 0.087 | 0.096 |
| | | (2.01) | (1.89) | (0.46) | (1.10) | (1.60) | (1.97) | (0.39) | (0.65) | (0.71) |
| Positive Current Expenses | | 1.096*** | 1.006*** | 0.553*** | 0.730*** | 0.886*** | 0.827*** | 0.416** | 0.524*** | 0.531*** |
| | | (6.71) | (6.09) | (2.84) | (4.38) | (5.42) | (4.95) | (2.16) | (2.68) | (2.67) |
| Fixed Effects (Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Regressors | | | | *Financials* | *Innovation* | *Team* | *Others* | *All* | *All* | *All* |
| Order of Polynomial | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 3 |
| N | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 |
| R-sq. | 0.051 | 0.079 | 0.082 | 0.111 | 0.108 | 0.114 | 0.095 | 0.154 | 0.174 | 0.190 |
| Within Group Adjusted R-sq. | 0.016 | 0.043 | 0.046 | 0.069 | 0.068 | 0.077 | 0.059 | 0.107 | 0.114 | 0.120 |

**Panel B: Dependent Variable=Scientist Judge Score**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Cumulative Equity Raised | 1.958*** | | 1.401*** | 0.822*** | 0.950*** | 1.248*** | 1.115*** | 0.612*** | 0.554*** | 0.512** |
| | (12.01) | | (7.58) | (4.10) | (5.14) | (6.81) | (5.90) | (3.12) | (2.78) | (2.54) |
| Positive Retained Earnings | | 0.759*** | 0.342 | -0.159 | -0.139 | 0.230 | -0.034 | -0.317 | -0.168 | -0.184 |
| | | (3.31) | (1.46) | (-0.65) | (-0.60) | (1.00) | (-0.14) | (-1.32) | (-0.68) | (-0.73) |
| Negative Retained Earnings | | 0.809*** | 0.066 | -0.010 | -0.202 | -0.030 | -0.149 | -0.185 | -0.107 | -0.157 |
| | | (3.79) | (0.29) | (-0.04) | (-0.88) | (-0.13) | (-0.64) | (-0.80) | (-0.45) | (-0.66) |
| Current Gross Profit | | 2.422*** | 2.260*** | 1.372*** | 1.899*** | 2.365*** | 1.821*** | 1.292*** | 1.206*** | 1.134*** |
| | | (10.82) | (10.14) | (4.27) | (8.26) | (10.70) | (7.63) | (4.13) | (3.79) | (3.54) |
| Current Gross Loss | | 1.012*** | 0.798*** | 0.199 | 0.481** | 0.780*** | 0.496** | 0.154 | 0.237 | 0.198 |
| | | (5.06) | (3.98) | (0.89) | (2.40) | (3.95) | (2.43) | (0.71) | (1.07) | (0.88) |
| Negative Current Expenses | | 0.705*** | 0.658*** | 0.442** | 0.400** | 0.576*** | 0.530*** | 0.353* | 0.382** | 0.396** |
| | | (3.87) | (3.64) | (2.31) | (2.25) | (3.24) | (2.94) | (1.89) | (2.03) | (2.09) |
| Positive Current Expenses | | 0.728*** | 0.449* | -0.064 | -0.017 | 0.322 | 0.225 | -0.146 | 0.004 | 0.041 |
| | | (3.12) | (1.91) | (-0.23) | (-0.07) | (1.39) | (0.95) | (-0.54) | (0.01) | (0.15) |
| Fixed Effects (Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Regressors | | | | Financials | Innovation | Team | Others | All | All | All |
| Order of Polynomial | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 3 |
| N | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 |
| R-sq | 0.107 | 0.142 | 0.157 | 0.188 | 0.204 | 0.190 | 0.170 | 0.245 | 0.261 | 0.270 |
| Within Group Adjusted R-sq | 0.043 | 0.079 | 0.095 | 0.121 | 0.141 | 0.127 | 0.108 | 0.177 | 0.181 | 0.180 |

## Panel C: Dependent Variable=Total Score

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Cumulative Equity Raised | 1.271*** | | 0.832*** | 0.460*** | 0.596*** | 0.768*** | 0.745*** | 0.397*** | 0.363*** | 0.308** |
| | (12.32) | | (7.14) | (3.66) | (5.12) | (6.71) | (6.26) | (3.25) | (2.94) | (2.48) |
| Positive Retained Earnings | | 0.588*** | 0.340** | -0.031 | -0.003 | 0.285** | 0.226 | -0.068 | 0.017 | 0.025 |
| | | (4.07) | (2.31) | (-0.21) | (-0.02) | (1.98) | (1.50) | (-0.46) | (0.11) | (0.16) |
| Negative Retained Earnings | | 0.498*** | 0.057 | 0.025 | -0.138 | -0.001 | 0.012 | -0.039 | 0.006 | 0.001 |
| | | (3.71) | (0.39) | (0.17) | (-0.95) | (-0.01) | (0.08) | (-0.27) | (0.04) | (0.01) |
| Current Gross Profit | | 1.270*** | 1.174*** | 0.880*** | 1.096*** | 1.314*** | 1.133*** | 0.903*** | 0.818*** | 0.744*** |
| | | (9.01) | (8.36) | (4.37) | (7.57) | (9.52) | (7.53) | (4.63) | (4.16) | (3.76) |
| Current Gross Loss | | 0.922*** | 0.794*** | 0.467*** | 0.607*** | 0.762*** | 0.622*** | 0.377*** | 0.453*** | 0.403*** |
| | | (7.32) | (6.29) | (3.34) | (4.82) | (6.18) | (4.85) | (2.77) | (3.30) | (2.90) |
| Negative Current Expenses | | 0.436*** | 0.408*** | 0.214* | 0.244** | 0.351*** | 0.362*** | 0.172 | 0.205* | 0.216* |
| | | (3.80) | (3.58) | (1.78) | (2.18) | (3.16) | (3.19) | (1.49) | (1.76) | (1.85) |
| Positive Current Expenses | | 0.949*** | 0.783*** | 0.307* | 0.431*** | 0.661*** | 0.586*** | 0.191 | 0.316* | 0.335* |
| | | (6.46) | (5.30) | (1.78) | (2.93) | (4.57) | (3.93) | (1.14) | (1.86) | (1.94) |
| Fixed Effects (Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Regressors | | | | *Financials* | *Innovation* | *Team* | *Others* | *All* | *All* | *All* |
| Order of Polynomial | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 3 |
| N | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 | 3195 |
| R-sq. | 0.119 | 0.162 | 0.175 | 0.215 | 0.223 | 0.222 | 0.188 | 0.281 | 0.301 | 0.316 |
| Within Group Adjusted R-sq. | 0.045 | 0.091 | 0.105 | 0.141 | 0.152 | 0.153 | 0.118 | 0.207 | 0.217 | 0.223 |

## Appendix C. VC Judges' Investment Rationale

We conducted a survey of VC judges to gather information about their backgrounds and how they evaluate a startup (we were unable to survey scientist judges due to their anonymous evaluation process). A VC judge was surveyed on the same day that they judged in the competition, and the details of survey can be found in Appendix A. Out of the 307 VC judges who participated in the two-year competition, we received 221 responses from 162 distinct VC firms. To ensure the accuracy and impartiality of the responses, we clearly stated in the survey that all information would be used solely for research purposes and would be anonymized. Notably, a judge may evaluate the startup in multiple years of the competition. After the competition, a small number of VC judges made investments in the ventures that they evaluated during the competition. Using data from Qichacha, we identified 82 financing deals in competing ventures where at least one of the investing institutions matches the affiliation of the VC investors evaluating the venture during the competition. Table C.1 summarize the results from the survey.

A key question in the questionnaire addressed the most relevant factors for investment. The factors provided by the VC investors in the survey are ranked as following: team, product & technology, market prospects, business model, financial and intellectual property. Notably, VC judges rate the financial and intellectual property dimensions, for which the application provides rich information, as the least important: only 15% to 17% of the respondents considered financials important, and less than 10% regarded intellectual property as significant in their investment decisions. In addition,

VC judges were also asked about the sectors in which they intended to invest. The top three popular sectors are Electronic Information, AI, and Internet/Mobile. Furthermore, 60% to 65% of the VC judges replied that they were assigned to sectors they intended to invest in during the competition.

One concern regarding the competition setting is that VC judges might evaluate ventures differently in competition compared to how they do in practice. To address this, we make use of the information collected in a survey of VC judges on the same day that they judged in the competition. Specifically, we analyze the survey sample to test the correlation between the unexplained portion of scores and factors each judge indicated as most relevant in the survey. If judges consistently apply the same investment ideology in both competition and practice, we would expect to observe a larger proportion of scores explained by the characteristics that they claimed to value. In our regression, we include judges' background information, such as education, work experience, overseas study experience, and gender. Additionally, we control for the performance of the VC firm that the judge is affiliated with, including capital raised in the past three years and whether it has had successful IPO exits.

Table C.2 presents the results from estimating regression models using the residuals of VC judge scores estimated from different models. We start with an all-variable model in column (1) and selectively include or exclude Financials, Innovation, and Team characteristics in columns (2) through (5). Across different model specifications, we find a robust, negative, and significant relationship with Financials, and Product & Tech, indicating that VC judges who prioritize these factors in screening indeed have a larger

portion of their scores explained (i.e., smaller absolute value of residuals) by the observable venture characteristics. Furthermore, results reveal that more experienced VC judges have a smaller unexplained portion of their scores, indicating their skills in processing noisy information from observable venture characteristics.

**Table C.1. Survey Results from VC Judges**

This table provides an overview of the survey conducted from VC judges, with results presented in two columns, one for each competition year. The upper section summarizes the sample construction, reporting the total number of VC judges contacted and the number of VC firms they represent, alongside the number of judges who responded and their corresponding VC firms. The lower section summarizes the specific responses to the questions in the VC questionnaire.

| | **2017 Competition** | **2018 Competition** |
|---|---|---|
| Number of VC Judges in Competitions | 155 | 152 |
| Number of VC Firms Represented in Competitions | 100 | 107 |
| Number of VC Judges in Survey Respondents | 107 | 114 |
| Number of VC Firms Represented in Survey Respondents | 75 | 87 |
| **Variable** | **Percentage of Respondents Said "Yes"** | |
| Was Judge of 2016 | 76.2% | 69.1% |
| Was Judge of 2017 | 100.0% | 77.5% |
| Was Judge of 2018 | 58.9% | 100.0% |
| | | |
| **Question: What are the Most Relevant Factors for Investment?** | | |
| Team | 88.8% | 89.5% |
| Financial | 15.0% | 16.7% |
| Product & technology | 78.5% | 78.1% |
| Intellectual Property | 6.5% | 8.8% |
| Market Prospectus | 64.5% | 61.4% |
| Business Model | 32.7% | 35.1% |
| **Question: Which Sectors Do You Intend to Invest in?** | | |
| Electronic Information | 57.9% | 54.4% |
| Internet/Mobile | 46.7% | 36.8% |
| Biotech | 38.3% | 39.5% |
| Advanced Manufacture | 35.5% | 37.7% |
| New/Clean Energy | 26.2% | 31.6% |
| New Materials | 30.8% | 33.3% |
| AI | 57.0% | 53.5% |
| FinTech | 16.8% | 14.0% |
| Culture & Media | 11.2% | 8.8% |
| **1**(Assignment of the Competition Aligned with Investment Intention) | 64.9% | 62.0% |
| **Education** | | |
| Bachelor | 15.0% | 15.8% |
| Master | 70.1% | 71.9% |
| PhD | 13.1% | 11.4% |
| **Experience of Investment** | | |
| 0-3 Yrs. | 7.5% | 7.9% |
| 4-7 Yrs. | 41.1% | 39.5% |
| 8-10 Yrs. | 24.3% | 25.4% |
| 10 Yrs. | 25.2% | 25.4% |
| **Studied Abroad** | 19.6% | 14.9% |
| **Female** | 11.2% | 12.3% |

| | | |
|---|---|---|
| **Type of Institution Working for** | | |
| Angel | 23.4% | 26.3% |
| VC | 56.1% | 45.6% |
| PE | 13.1% | 18.4% |
| **Affiliated Institution: The Amount of Capital Raised in Recent 3 Yrs. (CNY)** | | |
| 30 Million | 13.1% | 10.5% |
| 30-50 Million | 10.3% | 11.4% |
| 50-100 Million | 6.5% | 8.8% |
| 100-200 Million | 14.0% | 14.0% |
| >200 Million | 54.2% | 53.5% |
| **Affiliated Institution: Any Successful Exit via IPO** | 47.7% | 47.4% |

## Table C.2. Alignment between VC Judges' Scoring and Investments

This table presents regression results examining which VC judge characteristics correlated with a greater reliance on application information during their evaluations. The dependent variable is the absolute value of the residuals derived from the decomposition regression of VC judge scores. The independent variables are categorized into three sets: the first set of independent variables Investment Focus: these are indicators derived from the VC judge's survey responses regarding their most relevant factors for investment. The second set pertains to the VC judge backgrounds, and the third set focuses on the VC firm characteristics of the that the judge represents. Specifications (1)-(7) vary based on the specific regressors included. Standard errors are clustered at the competition and industry levels, with t-statistics provided in parentheses. * p < .10; ** p < .05; *** p < .01.

| **Dep. Var.=\|Residual VC Judge Score\|** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| ***Most Relevant Factor=*** | | | | | | | |
| Team | -0.614* | -0.542 | -0.659* | -0.715* | -0.542 | -0.491 | -0.666* |
| | (-1.66) | (-1.40) | (-1.72) | (-1.80) | (-1.44) | (-1.23) | (-1.77) |
| Financials | -0.877** | -0.856** | -1.179*** | -1.124*** | -0.889** | -1.123*** | -0.733** |
| | (-2.52) | (-2.36) | (-3.22) | (-2.97) | (-2.52) | (-2.95) | (-2.08) |
| Product &Tech | -0.459 | -0.374 | -0.601** | -0.576* | -0.449 | -0.625** | -0.355 |
| | (-1.64) | (-1.26) | (-2.02) | (-1.88) | (-1.57) | (-2.04) | (-1.24) |
| Intellectual Property | -0.297 | -0.080 | 0.287 | 0.455 | -0.185 | 0.333 | -0.335 |
| | (-0.88) | (-0.23) | (0.78) | (1.20) | (-0.54) | (0.88) | (-0.98) |
| Market Prospectus | -0.017 | 0.145 | -0.155 | -0.060 | 0.014 | -0.161 | 0.053 |
| | (-0.06) | (0.50) | (-0.54) | (-0.20) | (0.05) | (-0.55) | (0.19) |
| Business Model | -0.410 | -0.209 | -0.353 | -0.239 | -0.373 | -0.406 | -0.307 |
| | (-1.50) | (-0.74) | (-1.21) | (-0.80) | (-1.34) | (-1.38) | (-1.11) |
| Intended to Invest in the Applicant's Industry | -0.146 | -0.057 | -0.082 | -0.036 | -0.104 | 0.081 | -0.164 |
| | (-0.69) | (-0.26) | (-0.37) | (-0.16) | (-0.49) | (0.35) | (-0.77) |
| ***Judge background*** | | | | | | | |
| Degree | 0.259 | 0.132 | 0.200 | 0.049 | 0.302 | 0.186 | 0.114 |
| | (0.99) | (0.49) | (0.71) | (0.17) | (1.13) | (0.65) | (0.43) |
| Experience | -0.386** | -0.372** | -0.381** | -0.375** | -0.402** | -0.352** | -0.410*** |
| | (-2.49) | (-2.31) | (-2.26) | (-2.20) | (-2.54) | (-2.05) | (-2.61) |
| Studied Abroad | -0.100 | 0.198 | -0.179 | 0.187 | -0.073 | -0.168 | 0.196 |
| | (-0.34) | (0.62) | (-0.56) | (0.57) | (-0.24) | (-0.51) | (0.64) |
| Female | -0.490 | -0.767** | -1.024*** | -1.151*** | -0.413 | -1.177*** | -0.555 |
| | (-1.43) | (-2.17) | (-2.81) | (-3.09) | (-1.21) | (-3.22) | (-1.61) |
| ***VC Represented by Judge*** | 0.259 | 0.132 | 0.200 | 0.049 | 0.302 | 0.186 | 0.114 |
| Capital Raised in Recent 3 Years | 0.156 | 0.148 | 0.195* | 0.235** | 0.132 | 0.156 | 0.179* |
| | (1.63) | (1.49) | (1.91) | (2.25) | (1.36) | (1.50) | (1.85) |
| Successful Exit Via IPO | 0.566* | 0.522 | 0.869** | 0.774** | 0.571* | 0.810** | 0.492 |
| | (1.73) | (1.56) | (2.48) | (2.17) | (1.73) | (2.26) | (1.50) |
| *Regression Model* | | | | | | | |
| Category of variables | *All* | Only *Financials* | Drop *Financials* | Only *Innovation* | Drop *Innovation* | Only *Team* | Drop *Team* |
| Order of Polynomial | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| N | 3123 | 3123 | 3125 | 3125 | 3123 | 3125 | 3123 |
| R-sq. | 0.0269 | 0.0216 | 0.0272 | 0.0272 | 0.0233 | 0.0239 | 0.0256 |

## Appendix D. Heterogeneity of Judge Score across different industries

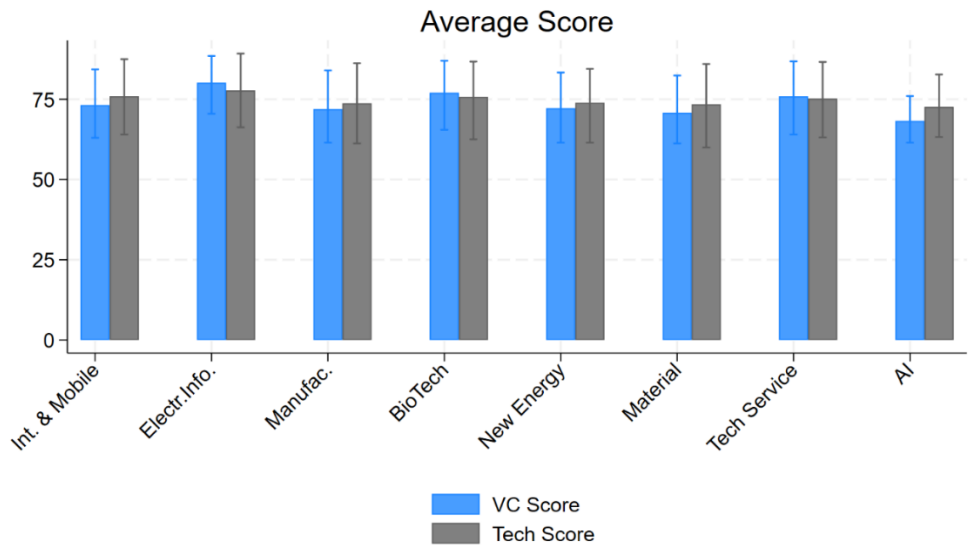



**Figure D.1. Average VC Judge and Scientist Judge Scores Across Industries**

This figure compares the average VC judge score and scientist judge score across eight distinct industries. The figure displays the average score, along with the 10th and 90th percentile values (represented by the error bars). The eight industries, classified according to the competition tracks are: internet and mobile devices (Int. & Mobile), electronic information (Electr. Info), advanced manufacturing (Manufac.), biological technology (Biotech), new energy resources (New Energy), new materials (Material), technology services (Tech Service), and artificial intelligence (AI).

## Appendix E- Robustness Tests

### Table E.1. Judge Score Prediction on Funding Outcome (excluding deals invested by VC judges)

This table presents the regression coefficients from Model (2), estimating the relationship between evaluations and subsequent fundraising success. The sample is restricted by excluding investment deals involving VC judges' affiliated firms. Specifications (1)-(4) use a binary indicator for funding deals (the extensive margin), while specifications (5)-(8) apply a logarithmic transformation (plus 1), representing the intensive margin. All specifications include three sets of fixed effects: competition year, VC judge panel, and industry. Standard errors are clustered at the competition and industry levels, with t-statistics provided in parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *1(Deals>0)* | | | | *ln(1+Deals)* | | | |
| VC Judge Score | 0.041*** | 0.041*** | | | 0.050*** | 0.050*** | | |
| | (6.15) | (6.28) | | | (5.46) | (5.57) | | |
| Scientist Judge Score | | 0.005 | | | | 0.007 | | |
| | | (0.83) | | | | (0.97) | | |
| Predicted VC Judge Score | | | 0.090*** | 0.098*** | | | 0.115*** | 0.125*** |
| | | | (7.47) | (6.82) | | | (6.89) | (6.27) |
| Residual VC Judge Score | | | 0.021*** | 0.020*** | | | 0.024*** | 0.023*** |
| | | | (3.57) | (3.52) | | | (3.10) | (3.05) |
| Predicted Scientist Judge Score | | | | -0.021 | | | | -0.027 |
| | | | | (-1.25) | | | | (-1.27) |
| Residual Scientist Judge Score | | | | 0.002 | | | | 0.002 |
| | | | | (0.26) | | | | (0.36) |
| Winner of Competition | 0.065*** | 0.056*** | 0.046** | 0.049** | 0.075*** | 0.063** | 0.051** | 0.055** |
| | (3.62) | (2.84) | (2.55) | (2.53) | (3.43) | (2.55) | (2.31) | (2.24) |
| Fixed Effects (Competition Year, Region, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3158 | 3158 | 3156 | 3156 | 3158 | 3158 | 3156 | 3156 |
| R-sq | 0.0667 | 0.0669 | 0.0801 | 0.0807 | 0.0636 | 0.0638 | 0.0794 | 0.0802 |

## Table E.2. Judge Score Prediction on Long-Run Innovation: Other Outcome Variables

This table presents the regression coefficients from model (2), examining the relationship between evaluations and innovation performance. The analysis is organized across Panels A through C, which feature different innovation outcome variables, including the number of certificates, copyrights, and awards. Specifications (1)-(4) are binary indicators that take the value of 1 for positive values, while specifications (5)-(8) apply a logarithmic transformation (plus 1). All specifications include three sets of fixed effects: competition year, VC judge panel, and industry. Standard errors are clustered at the competition and industry levels, and t-statistics are reported in parentheses. * p < .10; ** p < .05; *** p < .01.

### Panel A: Certificates

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *1(Certificates>0)* | | | | *ln(1+ Certificates)* | | | |
| VC Judge Score | 0.046*** | 0.050*** | | | 0.086*** | 0.093*** | | |
| | (4.53) | (4.92) | | | (4.48) | (4.90) | | |
| Scientist Judge Score | | 0.057*** | | | | 0.112*** | | |
| | | (5.66) | | | | (6.10) | | |
| Predicted VC Judge Score | | | 0.095*** | 0.019 | | | 0.218*** | 0.066** |
| | | | (6.33) | (1.11) | | | (7.50) | (1.99) |
| Residual VC Judge Score | | | 0.025*** | 0.035*** | | | 0.035** | 0.055*** |
| | | | (2.63) | (3.74) | | | (2.04) | (3.22) |
| Predicted Scientist Judge Score | | | | 0.228*** | | | | 0.452*** |
| | | | | (10.10) | | | | (10.66) |
| Residual Scientist Judge Score | | | | 0.010 | | | | 0.013 |
| | | | | (1.09) | | | | (0.79) |
| Winner of Competition | 0.095*** | 0.019 | 0.078*** | 0.007 | 0.204*** | 0.054 | 0.160*** | 0.026 |
| | (3.95) | (0.68) | (3.22) | (0.24) | (4.34) | (1.00) | (3.40) | (0.49) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 3205 | 3205 | 3203 | 3203 |
| R-sq. | 0.0769 | 0.0856 | 0.0825 | 0.1094 | 0.0891 | 0.0989 | 0.1001 | 0.1316 |

### Panel B: Software Copyright

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *1(Software Copyright>0)* | | | | *ln(1+ Software Copyright)* | | | |
| VC Judge Score | 0.035*** | 0.038*** | | | 0.084*** | 0.094*** | | |
| | (3.47) | (3.80) | | | (3.17) | (3.59) | | |
| Scientist Judge Score | | 0.045*** | | | | 0.148*** | | |
| | | (4.41) | | | | (5.50) | | |
| Predicted VC Judge Score | | | 0.087*** | 0.051*** | | | 0.217*** | 0.101** |
| | | | (5.92) | (3.03) | | | (5.30) | (2.22) |
| Residual VC Judge Score | | | 0.015 | 0.021** | | | 0.034 | 0.055** |
| | | | (1.62) | (2.27) | | | (1.38) | (2.23) |
| Predicted Scientist Judge Score | | | | 0.118*** | | | | 0.388*** |
| | | | | (5.02) | | | | (6.34) |
| Residual Scientist Judge Score | | | | 0.017* | | | | 0.063** |
| | | | | (1.85) | | | | (2.56) |
| Winner of Competition | 0.092*** | 0.032 | 0.075*** | 0.023 | 0.316*** | 0.119 | 0.272*** | 0.095 |
| | (3.94) | (1.21) | (3.17) | (0.87) | (4.79) | (1.59) | (4.08) | (1.27) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 3205 | 3205 | 3203 | 3203 |
| R-sq. | 0.0844 | 0.0897 | 0.0904 | 0.0981 | 0.1053 | 0.1129 | 0.1104 | 0.1215 |

### Panel C: Awards for Technological Achievements

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | | ***1****(Awards>0)* | | | | *ln(1+Awards)* | | |
| VC Judge Score | 0.046*** | 0.050*** | | | 0.064*** | 0.070*** | | |
| | (4.59) | (5.09) | | | (4.27) | (4.74) | | |
| Scientist Judge Score | | 0.067*** | | | | 0.097*** | | |
| | | (6.96) | | | | (7.42) | | |
| Predicted VC Judge Score | | | 0.121*** | 0.051*** | | | 0.197*** | 0.094*** |
| | | | (8.08) | (3.08) | | | (8.76) | (3.74) |
| Residual VC Judge Score | | | 0.018* | 0.028*** | | | 0.018 | 0.032** |
| | | | (1.95) | (3.12) | | | (1.30) | (2.41) |
| Predicted Scientist Judge Score | | | | 0.217*** | | | | 0.317*** |
| | | | | (9.84) | | | | (10.08) |
| Residual Scientist Judge Score | | | | 0.019** | | | | 0.023* |
| | | | | (2.20) | | | | (1.93) |
| Winner of Competition | 0.143*** | 0.053* | 0.119*** | 0.039 | 0.257*** | 0.127*** | 0.215*** | 0.104*** |
| | (5.95) | (1.94) | (4.92) | (1.44) | (7.23) | (3.21) | (6.07) | (2.67) |
| Fixed Effects (Competition Year, VC Judge Panel, Industry) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3205 | 3205 | 3203 | 3203 | 3205 | 3205 | 3203 | 3203 |
| R-sq. | 0.0976 | 0.1098 | 0.1094 | 0.1343 | 0.1170 | 0.1298 | 0.1352 | 0.1621 |

## Appendix F. Learning about Scientific Expertise through Competition Outcomes

This appendix formalizes how VC judges can infer scientific assessments from competition outcomes despite scientist scores being confidential. It also distinguishes learning from scientific expertise from alternative explanations such as learning about other VC judges' opinions or generic attention/effort effects, and derives the empirical predictions tested in Table 6 (regression equation (4)).

### F.1 Setup and scoring behavior

Each startup $i$has two latent quality components:

- Scientific (technological) quality: $\theta_i \sim \mathcal{N}(0, \sigma_\theta^2)$
- Market (commercial) quality: $v_i \sim \mathcal{N}(0, \sigma_v^2)$

**Scientist score (one judge)**

A single scientist judge evaluates the startup:

$$s_i^{Sci} = \theta_i + \varepsilon_i^{Sci}, \varepsilon_i^{Sci} \sim \mathcal{N}(0, \sigma_{Sci}^2).$$

Scientist scores are never disclosed to VC judges.

**VC scores (three-judge panel)**

Three VC judges $m \in \{1,2,3\}$independently evaluate the startup:

$$s_{im}^{VC} = v_i + \varepsilon_{im}^{VC}, \varepsilon_{im}^{VC} \sim \mathcal{N}(0, \sigma_{VC}^2) \text{ iid.}$$

The competition uses the **average VC score**:

$$\bar{s}_i^{VC} = \frac{s_{i1}^{VC} + s_{i2}^{VC} + s_{i3}^{VC}}{3} = v_i + \bar{\varepsilon}_i^{VC}, \bar{\varepsilon}_i^{VC} \sim \mathcal{N}\left(0, \frac{\sigma_{VC}^2}{3}\right).$$

A given VC judge $j$observes her own score $s_{ij}^{VC}$only if she evaluates startup $i$. She does not observe the scientist score nor the other VCs' scores.

### F.2 Final index and winning rule

Consistent with the competition design, the final index is a deterministic weighted average:

$$T_i = 0.4\, s_i^{Sci} + 0.6\, \bar{s}_i^{VC},$$

and the publicly observed outcome is:

$$W_i = \mathbf{1}\{T_i \geq c\}.$$

Although there is no mechanical error term in $T_i$, from the perspective of an individual VC judge the index is uncertain because key components are unobserved.

### F.3 What information is embedded in winning status?

When VC judge $j$evaluates startup $i$, she observes $s_{ij}^{VC}$and $W_i$. Rearranging the index:

$$0.4\, s_i^{Sci} + 0.6 \cdot \frac{2}{3} \bar{s}_{i,-j}^{VC} \geq c - 0.2\, s_{ij}^{VC},$$

where

$$\bar{s}_{i,-j}^{VC} \equiv \frac{1}{2} \sum_{m \neq j} s_{im}^{VC}.$$

Thus, conditional on her own score, winning status provides information about a composite unobserved term that includes:

1) the scientist's private assessment $s_i^{Sci}$; and
2) the average assessment of the other two VC judges $\bar{s}_{i,-j}^{VC}$.

This motivates the concern that VCs might learn primarily about *other VCs' opinions* rather than about scientific expertise.

### F.4 Posterior learning about scientific quality

#### F.4.1 Judged ventures

If VC judge $j$evaluated startup $i$, she conditions on $\{s_{ij}^{VC}, W_i\}$. Subtracting her own mechanical contribution yields the residual index:

$$R_{ij} \equiv T_i - 0.6 \cdot \frac{1}{3} s_{ij}^{VC} = 0.4\, s_i^{Sci} + 0.6 \cdot \frac{2}{3} \bar{s}_{i,-j}^{VC}.$$

Substituting the signal structure:

$$R_{ij} = 0.4\, \theta_i + \underbrace{0.4\, \varepsilon_i^{Sci} + 0.4\, v_i + 0.4\, \bar{\varepsilon}_{i,-j}^{VC}}_{\text{noise from VC } j\text{'s perspective}}.$$

The event $W_i = 1$is equivalent to:

$$R_{ij} \geq c - 0.2\, s_{ij}^{VC}.$$

Since $(\theta_i, R_{ij})$are jointly normal, the posterior mean of scientific quality conditional on winning is:

$$\mathbb{E}[\theta_i \mid s_{ij}^{VC}, W_i = 1] = \frac{0.4\, \sigma_\theta^2}{\sigma_{R,J}} \cdot \lambda\left(\frac{c - 0.2\, s_{ij}^{VC}}{\sigma_{R,J}}\right),$$

where $\lambda(\cdot)$is the inverse Mills ratio and

$$\sigma_{R,J}^2 = 0.16(\sigma_\theta^2 + \sigma_{Sci}^2 + \sigma_v^2 + \sigma_{VC}^2/2).$$

Define the **belief loading for judged ventures**:

$$\kappa_J \equiv \frac{0.4\,\sigma_\theta^2}{\sigma_{R,J}}$$

### F.4.2 Non-judged ventures

If VC judge $j$did not evaluate startup $i$, she conditions only on $W_i$. From her perspective:

$$T_i = 0.4(\theta_i + \varepsilon_i^{Sci}) + 0.6(v_i + \bar{\varepsilon}_i^{VC}), \bar{\varepsilon}_i^{VC} \sim \mathcal{N}\left(0, \frac{\sigma_{VC}^2}{3}\right).$$

Then:

$$\begin{aligned}&\mathrm{Cov}\,(\theta_i, T_i) = 0.4\,\sigma_\theta^2,\\ &\sigma_{T,NJ}^2 = 0.16(\sigma_\theta^2 + \sigma_{Sci}^2) + 0.36(\sigma_v^2 + \sigma_{VC}^2/3).\end{aligned}$$

The posterior mean conditional on winning is:

$$\mathbb{E}[\theta_i \mid W_i = 1] = \frac{0.4\,\sigma_\theta^2}{\sigma_{T,NJ}} \cdot \lambda\left(\frac{c}{\sigma_{T,NJ}}\right).$$

Define the belief loading for non-judged ventures:

$$\kappa_{NJ} \equiv \frac{0.4\,\sigma_\theta^2}{\sigma_{T,NJ}}$$

### F.5 Core comparative static

Observing one's own VC score allows a judging VC to partial out part of the VC component in the index, making win/loss a sharper signal about the remaining unobserved components, including scientific quality. Formally,

$$\sigma_{T,NJ}^2 > \sigma_{R,J}^2 \Rightarrow \kappa_J > \kappa_{NJ}.$$

Thus, competition outcomes are more informative about scientific quality for judged ventures than for non-judged ventures.

### F.6 Competing learning channels and empirical predictions

**Learning from scientific expertise**

If VCs use competition outcomes to infer the scientist's private assessment, then investment decisions should become more sensitive to scientific private information when the VC judged the venture. If we focus on the residual (private-information) component of the scientist score observed by the econometrician. Along with the specification (4) (corresponding to results reported in Table 6)

The model implies:

$$\gamma_J^{Sci,res} \propto \kappa_J, \gamma_{NJ}^{Sci,res} \propto \kappa_{NJ}, \gamma_J^{Sci,res} > \gamma_{NJ}^{Sci,res}$$

**Learning from other VC judges (alternative explanation)**

If judged exposure mainly reveals whether *other VCs* liked the venture, then investment decisions should become more aligned with VC-side private information, not with the scientist's private signal.Under this channel, judged exposure predicts:

$$\beta_{VC,res}^{J} > \beta_{VC,res}^{NJ}$$

There is no specific reason under this mechanism for the slope increase to concentrate on the scientist residual component.