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

Suting Hong
ShanghaiTech University

Su Wang
ShanghaiTech University

Xiang Yin
Tsinghua University

October 2024

Abstract

Assessing innovative start-ups at an early stage poses critical challenges. We explore whether technology-oriented experts are more capable than venture capitalists (VCs) in screening high-tech ventures. Using administrative data from a prestigious start-up competition in Shanghai China, where both VCs and scientists evaluate high-potential ventures for government grants, we find that the two groups of judges utilize distinct private information and approaches to assessing ventures. Furthermore, compared to VC evaluations, scientist evaluations are better predictors of a start-up's subsequent innovation performance. Empirical analysis suggests that the insights from technical experts, typically inaccessible to VCs, would render value if integrated into the screening process. Our study underscores the importance of technology-proficient human capital in improving the efficacy of identifying high-potential start-ups.

Key words: venture capital, screening, R&D human capital, innovative start-up, new venture competition.

JEL: G24, G32, L26, O31, J24.

* Suting Hong (hongst@shanghaitech.edu.cn); Su Wang (wangsu@shanghaitech.edu.cn); Xiang Yin (yinxiang@sem.tsinghua.edu.cn).

We thank Catherine de Fontenay, Jeff Furman (discussant), Po-Hsuan Hsu, Josh Lerner, Bo Li (discussant), Xiyue Li (discussant), Scott Stern, audiences in presentations at the 2024 NBER-AIEA Conference, the 7th Indonesian Financial Management Association (IFMA) Annual International Conference, the 2024 China Financial Research Conference, the 2024 China Financial Research Network Young Scholar Forum, the 2024 Chinese Economist Society Conference, and Zhejiang University for helpful comments. All errors and omissions are our own.

1. Introduction

Assessing the potential of start-ups at an early stage poses serious challenges, even for seasoned venture capitalists (VCs). Investing in innovative startups is fraught with extreme *ex-ante* uncertainty and highly skewed *ex-post* returns, where a small number of investments drive the majority of VC portfolio returns (Knight, 1921; Kerr et al., 2014). Over the past two decades, the VC industry has seen a diversification of skills among general partners, with a growing influx of individuals into the profession holding PhDs in science, technology, engineering, and math (STEM). [1] Analysis using Pitchbook data reveals that STEM PhD holders achieve a 20% success rate in bringing their portfolio companies to high-status exits, significantly outperforming those with non-STEM or lower-level STEM degrees, who have on average a 12% success rate. [2] This performance advantage of scientist-investors is particularly pronounced in early-stage investments and technology-intensive sectors, underscoring the value of high-quality human capital in STEM fields in the VC industry.

Given the industry-wide challenges in identifying high-potential ventures, understanding the advantages of scientist-turned-investors, particularly in screening early-stage entrepreneurial projects, is critical. This study asks whether technical experts are more capable than VCs in evaluating high-quality startups, focusing on three key aspects: 1) the discrepancies between evaluations from VCs and technology-oriented experts; 2) the source of these divergences, and 3) the relationship between these evaluations and subsequent venture

[1] Such a trend seems to be driven by both demand and supply: the VC industry advocates more scientists to join the profession while PhDs trained in hard-core sciences have also turned their interests to a career in the industry and often find it a good fit with their academic experience.
(https://tech.eu/2024/02/10/europe-needs-more-scientists-in-vc-to-become-a-deep-tech-powerhouse/; https://www.science.org/content/article/preparing-career-venture-capital, accessed August 2024)
There is also a higher need for deeper technical due diligence in venture capital.
(https://www.fastcompany.com/90782813/vcs-will-need-deeper-technical-due-diligence-capabilities, accessed August 2024).

[2] The calculation considers active investors worldwide from 2007 to 2015 for whom Pitchbook provides educational background information (i.e., degree types and fields of study). The classification of STEM degrees is according to the STEM designated degree program list provided by the U.S. Department of Homeland Security. 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), success is defined as either an IPO or a high-value acquisition (with at least twice the amount of total investment received) of the portfolio company. See Appendix A for a detailed breakdown of the success rates of different types of VC investors by educational background.

performances. However, answering the questions above is constrained by several limitations, such as the availability of independent evaluations from tech-oriented evaluators and market-oriented VCs, the opacity of venture characteristics at the time of evaluation, and the lack of data on the post-evaluation growth trajectory of startups. Additionally, focusing exclusively on VC-backed ventures limits our ability to understand the counterfactual outcomes of ventures not selected by VCs.

To overcome these challenges, we utilize administrative data from the prestigious China Innovation and Entrepreneurship Competition, specifically the regional-level tournaments in Pudong District, Shanghai. This district is one of China's leading innovation hubs, known for its significant clusters of high-tech ventures in fields such as semiconductors, biotechnology, pharmaceuticals, and artificial intelligence.[3] A key feature of the Pudong District competition is its dual evaluation system: two scientists with R&D backgrounds (either in academia or industry) assess the ventures *exclusively* based on their profiles, while three VC judges evaluate the business through *both* profile reviews and pitch presentations. Importantly, judges are blind to each other's scores, and the final winners are determined by a weighted average of the two types of evaluations. The competition concludes with a public announcement of the winners, without disclosing numerical rankings or detailed scores to the participants.

Our sample contains 3,205 high-tech start-ups that participated in the competition in 2017 and 2018. These startups have, on average, four years of operational history and 22 employees. The data include detailed self-reported financial and operational information for the three years preceding the competition[4], as well as the evaluation scores from both scientists and VC judges—information that remains inaccessible to the contestants. Additionally, we surveyed the VC judges to understand their preferences for venture characteristics during screening. To

[3] Since its first launch in 2012, the China Innovation and Entrepreneurship Competition has attracted participation from over 280,000 ventures. As the largest of its kind in scale nationwide, this competition consists of both regional and national levels of tournaments.

[4] Since the competition is launched and administered by the Shanghai Municipal Government, contestants have minimal incentives to submit false application profiles.

track the post-competition trajectories of the contestants, we collected data on external financing and innovation outcomes from Qichacha and Incopat up to January 2024.[5]

We first examine whether VC and scientist judges use the same set of information in their evaluations. For each type of judge, we regress their scores on observable venture characteristics and obtain predicted scores which reflect evaluations based on information available to all who have access to the company profiles. The residual scores represent the portion of the evaluations based on private information unique to each judge type. We find distinct screening approaches between VCs and scientists: a correlation of only 0.5 between their predicted scores suggests they process common information differently. In addition, the near-zero correlation between their residual scores suggests that VCs and scientists draw on distinct sources of private information in their evaluations. This aligns with the competition's structure, where VCs have the opportunity to gather extra information by observing pitches from the founding teams.

We then examine how the two types of judges utilize commonly available information. First, across a variety of specifications we fit, observable venture characteristics consistently explain a significantly higher proportion of variation in scientist judges' evaluations compared to scientists' scores, suggesting scientist judges rely more on the commonly available information.[6] Furthermore, the two types of judges weigh observable characteristics differently, as evidenced by the distinct estimates for venture characteristics.[7] Last, VC judges employ a more sophisticated methodology than scientists when processing commonly available information. This is evident in the regression analysis, where VC judges' adjusted R-squares always increase with higher-order polynomials, while scientists' scores stabilize after the second order. Consistent with these findings, our analysis of the survey data confirms that VC

[5] 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.

[6] This result holds for a saturated model controlling for competition year and judge panel fixed effects and when we control for more complex relationships in the data by incorporating higher-order terms of observable characteristics up to the 10th power.

[7] VC judges value firm capitalization, current profits (for both negative and positive values), and higher expenses; in contrast, scientists focus primarily on capitalization and positive gross profits.

judges apply their investment philosophy developed through practical experience to evaluate ventures, supporting the external validity of our research design for real-world investments.

We further analyze the long-term predictive power of judge evaluations by tracking post-competition firm innovation and financing outcomes. All three score types (i.e., weighted total, VC, and tech) positively predict the innovation outputs of a contestant venture, including patent applications, certificates, software copyrights, and awards for technological achievements. Notably, scientists' scores exhibit stronger predictive power than VC scores for all the innovation output measures considered. Furthermore, scientist scores significantly predict the quality of patent output, as proxied by forward citations, whereas VC judge scores fail to show such predictability. This highlights the value from scientist judges' evaluations in identifying innovative ventures of high potential. However, scientist judges' scores are only weakly associated with the chance of receiving future VC financing or commercialization outcomes (as measured by trademarks received) of the venture, pointing to a misalignment between scientific evaluations and real-world VC investment decisions.

We examine the relationship between judge scores and actual VC investment by judges in contestant startups. We analyze all potential pairs between a contestant venture and a VC who judged the competition. Both weighted total and VC scores are positively associated with the likelihood of a VC judge investing in a venture at a later time, regardless of whether they judged the focal venture in the competition. In the meantime, the predictive power of scientist scores on future funding are low and insignificant, suggesting VCs rarely consider tech scores in their investment decisions, likely due to the fact that VC and tech evaluators do not observe each other's scores.

We then explore the contingency of the scientist scores' predictive power on VC investments. A higher score from scientist judges is significantly and positively associated with the likelihood for a VC investing in a start-up *only if* the VC has served as a judge in the venture's pitch competition. This suggests that VCs likely consider scientist judges' evaluations when investing in ventures that they have reviewed in the competition, possibly

inferring scientists' scores from observing the competition outcome (which is decided by the weighted average of tech and financial scores). If the VC does not review the venture as a judge, however, scores from the scientist judges do not affect their investment decisions, likely due to VCs' limited access to the scientist judge's assessments. This implies that, while VCs generally lack insights from the scientist judges regarding a venture's potential, they would likely value and apply these insights if made available.

Our paper contributes to four strands of literature. The first concerns human capital in the VC industry. Prior studies have shown that experienced VCs lead to better portfolio outcomes, largely due to their superior screening abilities (Lerner 1994; Nahata 2008; Hsu 2004; Sørensen, 2008). Recent research, using micro-level data, examines how individual characteristics like industry specialization, gender, and personal connections influence VC deal performances (Gompers et al., 2008, 2016, 2022). Leveraging the unique setting of the Pudong innovation competition, our paper asks how investors with technology expertise differ from VCs in screening early-stage ventures, and whether they can better identify ventures of high innovative potential.

The second strand of literature investigates VCs' impacts on innovation. While VC investments are linked to increased venture patenting (Kortum and Lerner, 2001), recent studies highlight their limitations in driving major technological advances, especially during economic downturns when VCs favor more profitable, less innovative firms (Lerner and Nanda, 2020; Howell et al., 2020; Ewens et al., 2018).[8] Our paper shows that VC and scientist evaluations are distinct as suggested by their low levels of correlations. Notably, experts with technology proficiency are better at predicting future innovation outcomes than VCs. Additionally, our findings raise concerns about the use of algorithms in VC screening, as algorithms may focus on historical data rather than identifying truly groundbreaking ventures (Bonelli, 2023; Lyonnet and Stern, 2022).

[8] Lerner and Nanda (2020) point out that VCs' focus on only a narrow range of innovation is driven by the need to quickly resolve the uncertainty about market demand for new product or service. Abuzov (2019) finds that VCs tend to make underperforming investments when they are busy and distracted. Moreover, the common ownership structure of VCs' portfolios may lead to redirection in innovation at lagging startups (Li et al., 2023).

Third, our study relates to the literature on the screening of innovative startups and the role of accounting information in the process (Armstrong, Davila, Foster, and Hand, 2007; Cassar, 2009; Davila and Foster, 2007; Beuselinck, Elfers, Gassen, and Pierk, 2023). VCs select ventures where they can add value through monitoring and support (Kaplan and Strömberg, 2001; Gompers and Lerner, 2001), and also highlight the importance of founding teams over business traction or existing investors in early-stage funding decisions (Baron and Hannan, 2002; Bernstein et al., 2017; Gompers et al., 2020; Hellmann and Puri, 2000). Our findings indicate that VCs prefer ventures with higher equity funding raised and gross profits (or losses), but are less sensitive to firm characteristics than scientist judges in evaluating innovative startups. Furthermore, building upon Kisseleva, Mjos, and Robinson (2024), who demonstrate that the lagged book value of equity influences valuation across financing rounds, our work underscores the relevance of information in uncertain, innovative contexts. Importantly, VCs' assessments are not solely based on readily available financial information; they also substantially incorporate private information, highlighting VCs leverage their expertise and non-public insights in making investment decisions.

The last strand of literature studies new venture competition, a growing trend among intermediaries supporting early-stage startups (Howell, 2020). While previous literature has focused on accelerators (Hochberg and Fehder, 2015; Gonzalez-Uribe and Leatherbee, 2017; and Gonzalez-Uribe and Rynes, 2021), incubators, and crowdfunding platforms (Yu, 2020), new venture competitions have received limited academic attention despite their global proliferation. This study leverages a unique competition in Shanghai, featuring evaluations from both scientists and VC judges, to offer insights into the diverse human capital within the VC industry and the design mechanisms of competitions aimed at enhancing their efficacies.

The remainder of the paper is organized as follows: Section 2 introduces the institutional backgrounds. Sections 3 describes the data and sample. Section 4 introduces the empirical methodology. Section 5 presents key differences in how VCs and scientists assess early-stage ventures. Section 6 demonstrates how these evaluations predict a venture's subsequent

performances, and discusses the link between judge evaluations and VC investment decisions. Section 8 concludes.

2. Institutional Backgrounds

2.1. Startup in Shanghai Competition

The Ministry of Science and Technology of China has been organizing the China Innovation and Venture competition on an annual basis since year 2012, the largest of its kind nationwide. It consists of both regional and national tournaments. Our data come from the regional-level tournament in Shanghai, known as "Startup in Shanghai". Each district within the Shanghai municipality runs its own competition, and only companies registered in the respective district are eligible to participate. Furthermore, according to the size of the ventures (i.e., incomes and number of employees), contestant ventures are divided into two categories: small & micro ventures and growth-stage ventures. Each group competes separately at the district level.

In our study, we focus on the small & micro venture group, which adheres to the following participation criterion: (i) the venture must have generated no more than 30 million RMB in revenue in the fiscal year preceding the competition; (ii) it must employ no more than 300 people, with at least 10% engaged in R&D activities by the end of the previous fiscal year; (iii) the ratio of R&D expenditures over incomes is at least 5% for the last fiscal year. "Startup in Shanghai" has only one round of competition: the winners of the district-level contests are directly declared as the overall winners of "Startup in Shanghai" without further rounds of contests. These winners receive a 100,000 RMB grant from the municipal-level Innovation Fund for Small and Medium Technology-based Firms (commonly known as Innofund; Wang et al., 2017) and an additional 100,000 RMB grant matched by the local district government. Additionally, the top-ranked winners qualify for entry into the national-level Innovation and Venture Competition.

Our sample includes all startups that competed in the micro & small venture group in Pudong New District competitions in 2017 and 2018. Pudong New District, the largest

district in Shanghai by economic activity, accounted for approximately one-third of the city's GDP during our sample period. As a state-level new district, Pudong receives special economic and development support from the Chinese central government, including favorable tax policies and initiatives aimed at attracting high-skilled talent. The district hosts four state-level special economic zones: Lujiazui Finance and Trade Zone, China (Shanghai) Pilot Free Trade Zone, Jinqiao Export Processing Zone, and Zhangjiang Hi-Tech Park. Over time, Pudong has developed world-class industrial clusters in integrated circuits, biomedicine, and artificial intelligence. These factors have made Pudong one of the most dynamic areas for entrepreneurship in China, particularly in the technology sector. This is also reflected in the industry composition of the competing ventures, which 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.

Regarding the motivations for start-ups to participate in the competition, we surveyed all ventures that competed in 2018. With a corresponding rate of 62%, the results suggest that entrepreneurs enter the competition for several non-mutually exclusive reasons, with the most common being the pursuit of winning the grant (selected by 87% of respondents). Other notable motivations, ranked second and third, include enhancing the reputation for their products/services (71%) and receiving feedbacks from judges to support venture growth (68%). Furthermore, we interviewed 20 entrepreneurs in the year of 2018. When asked about their motivation for winning the grant, the founders mentioned several benefits associated with the certifications awarded in a government-backed competition. These include improved reputations among customers and potential collaborators, access to low-interest loans, and building connections with venture capital investors. Meanwhile, the grant amount (200,000 RMB) is relatively modest compared to the average income levels of competing ventures in the sample (3.7 million RMB), suggesting that the primary benefits lie in the certifications rather than the monetary award itself.

Upon signing up for the competition, all contestant startups are required to submit details on firm registration, team composition, technology or product, financials, and business plans to a government-maintained database. Outlines of the required information are provided in Appendix B. By examining the application materials from ventures that competed in 2017 and 2018, we found that 9.5% had received equity funding and 2.3% had received debt funding prior to the competition.

2.2. Judges and Evaluation Procedure

Each venture is assigned two tech-focused reviewers responsible for evaluating the technology potential and feasibility of the project. The Science and Technology Commission of Shanghai Municipality (STCSM) assigns these reviewers by randomly selecting from their repository of research and development (R&D) experts who are experienced academics or industry researchers. According to the public announcement by STCSM, to be included in the repository, individuals must meet at least one of the following criteria: 1) hold the title of associate researcher or researcher; 2) serve as the principal investigator for a grant project funded by a provincial-level science & technology commission (such as STCSM in Shanghai) or national research institutions (such as natural science foundation of China); 3) recipient of provincial or national awards in science or technology.[9] These criteria highlight the high level of R&D expertise of the tech reviewers. Furthermore, each venture is assigned reviewers with expertise relevant to the industry field of the competing project. The technology reviewers have access to the full application packet of each venture, and likely focus on the details in the business plan and core technology description to make their assessments. Additionally, the identity of technology reviewers remains secret to contestant ventures throughout the competition.

The other component of the evaluation comes from VC judges who are professional investors managing venture capital (VC) or angel funds. Like the technology reviewers, the VC judges have access to the competing venture's application packet but also attend a 15-

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

minute pitch. At each local pitch event, all participating ventures belong to the same industry category, and a panel of judges with expertise in that specific industry is assembled for the day's competition. VC judges do not know in advance which ventures they will evaluate, nor do the contestant ventures know in advance who the judges will be. During the pitch, VC judges remain anonymous to the contestants and assign scores immediately after the presentation. All judges in a panel independently score projects with no discussion allowed.

Contestant ventures are ranked by a weighted average score plus a bonus score. The weighted average score is calculated from two sets of 100-point raw scores: 40% comes from the technical experts, and 60% comes from the VC judges. An additional 1 to 3 bonus points are added to the 100-point weighted average based on specific criteria, such as a sales growth rate of over 20% in the previous year. While contestant ventures are aware of the 1-3 bonus points, they are not informed of the exact criteria. As researchers, we have access to both the criteria and the ventures that received these bonus points. There is no evidence suggesting that bonus points influence the likelihood of winning. Since bonus points account for only a small portion of the total score (1-3 points vs. 100 points), they are fairly distributed across a broad range of weighted average scores, with the cutoff score for winning typically falling near the middle.

Notably, we have access to scoring and ranking information, which is kept confidential from competition participants and judges. Winners are only informed of their winning status, not their scores or ranks. Each year, about one-third of the contestant ventures received a total grant of 200,000 RMB in the Pudong District competition. The list of winners is published online by the STCSM. Among these winners, about 10% — the top performers—qualify for entry into the national-level competition. These winners can infer that they are among the highest-ranked ventures.

3. Data and Sample

We draw our sample from the aforementioned application data and the internal administrative records of scores and ranking. The sample consists of three primary sets of

variables: (1) firm-level information about the contesting ventures; (2) resume information of the core team members; (3) confidential evaluation records, including the pitch-day assignment of VC judge panels, raw scores (from tech-oriented and VC judges as well as bonus points), final total scores, and winner status. We further search in the external databases to match the contestant ventures to their subsequent funding outcomes and innovation outputs. Specifically, information on funding events is retrieved from Qichacha, a leading Chinese company information query platform that provides comprehensive data on Chinese companies, including business registration, financial statements, legal cases, and intellectual property information. We further supplement information on patent grants and citations from Incopat, which collects data on intellectual property from over 157 patent offices worldwide, offering access to over 180 million patent documents. Additionally, we surveyed all VC judges about their preferences and evaluation criteria for assessing contestant ventures. The survey was conducted on the same day that a judge participated in the pitch competition.

3.1 Application Information

Upon the application, startups participating in the competition were required to fill in electronic application form that spans most key financial and economic information of them (see Appendix B for outlines of the form). Table 1 provides a summary of the statistics of the main variables used for the analysis.

There are 3,205 participant startups in the year 2017 and 2018 competitions. The industry breakdown of these startups, as shown in Panel A of Table 1, illustrates the landscape of innovative entrepreneurship in Shanghai. The top three industries are “Internet and Mobile”, “Electronic Information” and “Advanced Manufacturing”. Also, there is a significant distinction in the distribution of participant industries between 2017 and 2018, suggesting entrepreneurship occurs in waves.

As shown in Table 1, most of the firms in our sample are young and small. About 75% of the firms were under five years old and had less than 26 employees at the time of the competition. The median age is three years, with a median employee count of 15, which is

relatively small for startups in the high-tech industry. According to balance sheet information, at median level, a startup in the sample has total assets of 1,627,000 RMB (about 228,600 USD). Leverage is low, with a median total liabilities value of 58,000 RMB (about 8,150 USD). Receivables and inventory are minimal, as most startups do not even have production lines at this stage. The level of tangible assets is low, reflecting the innovative nature of the startups in our sample.

The income statement offers insights into the cash flows of these startups. Most of them have negative net profit, with a median net profit of -157,000 RMB (-22,060 USD). This is mostly driven by the high level of various operating expenses rather than inefficient production process, as gross profits are mostly positive. This pattern is typical for startups engaged in research and development and professionalization, which necessitate significant overhead costs.

Following Kisseleva, Mjøs, and Robinson (2024), we propose that the evaluation of startups should be benchmarked against disaggregated book equity value, which provides crucial insights into their financial health. Book equity value can be disaggregated into cumulative capital, retained earnings, and current profits. Furthermore, we break down current profit/loss into gross profit/loss and expenses[10]. Table 1 presents summary statistics of the disaggregated book equity value, aligning with the cash flow lifecycle of early-stage firms: those competing firms predominantly present positive gross profits and negative cash flows that exceed gross profits due to various expenses. As a result, most of them show negative retained earnings.

We also assess the startups' innovation performance across several dimensions. The application form requires the participant to fill in information on different types of intellectual property, including patents, software copyrights, Integrated Circuit Layout (ICL) Designs, marketable drugs, and certificates of medical devices. About 75% of competition participants have no intellectual property at the time of the competition. At the median, 9 employees are

[10] 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".

engaged in R&D, while 13 employees hold bachelor's degrees or higher, based on a median total employee count of 15. This indicates a strong presence of knowledge-intensive human capital within these ventures. Additionally, numerous national and regional support programs act as certifications and accelerators of these startups' innovation capacity. These indicator variables serve as proxies for the current innovation capabilities of the startups.

The application form also collects demographic and resume information for the founding teams. Each venture must provide detailed information for at least three core members. From this data, we extract several variables that characterize these individuals. Entrepreneurs in our sample have a median age of 39, with 92% holding a degree above a bachelor's level and 53% possessing a master's or doctoral degree. Additionally, 22% have studied abroad, and more than 50% have previously founded a business.

3.2 Judge Scores

As explained in Section 2, we have access to administrative records of scoring and ranking information for 2017 and 2018 competitions. As an initial check, we examine the correlation between the evaluation scores given by the two types of judges. Figure 1 illustrates the correlations between the two scores for both years. The correlation coefficients are around 0.25. This suggests that, while VC judges and technology judges share some common perspectives when evaluating startups, there are also distinct components in the scores that are unique to each group. The average score for VC judges is 74.43, with a standard deviation of 9.20, while scientist judges have an average score of 75.39 and a standard deviation of 9.60.

3.3 Survey on VC Judges

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. 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.[11] 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 2 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.

Demographic information of judges show 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 landscape of investors interested in young, innovative startups. Most are VC funds, alongside some angel investors and a small number of PE 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.

3.4 Post-Competition Performance

[11] For the 2017 (2018) competition, 100 out of 155 (107 out of 152)VC judges responded to the survey..

We extracted performance information for the sample of participant firms from the year of competition up to January 2024. The variables are classified into three categories: innovation outputs, fundraising, and credit risk. We tracked the innovation activities of the startups by examining patent applications and grants, professional and technical certificates, software copyrights, and awards for innovation and scientific achievements. We also utilize information on VC financing deals and trademarks obtained by a venture. The latter often signals the commercialization of products followed by VC funding (Chemmanur et al., 2023).

Table 3 summarizes the variables that describe post-competition venture performances. Innovation activities are pervasive among these startups. 45% have applied for patent since the competition. Even when excluding applications made before the first VC funding post competition, 42% have still filed patent applications, with a grant rate of approximately 80%. Additionally, 47% of the startups have been awarded professional and technical certificates, and 54% have secured software copyrights since the competition. Furthermore, 44% of the startups have received national or regional scientific awards for their achievements. Overall, the innovation performance of this sample of startups is quite high. Regarding financing and commercialization, 12% of these startups have secured at least one financing deal after the competition, and 43% have obtained at least one trademark.

4. Empirical Methodology

4.1 Differences in Evaluations from Judges

While the relatively small correlation between the scores provided by financial and technical experts suggests significant differences in their evaluations, the specific dimensions and sources of these differences remain unclear. To better understand the distinct ideologies driving their assessments of startups, we decompose the scores into two independent components. Specifically, motivated by previous studies that highlight the roles played by public information and private information in financing decisions (e.g., Armstrong et al., 2007), we hypothesize that startup evaluations are influenced by both the observable information provided in the application forms and the private information held by the judges. For startups,

the hard information submitted in their competition applications is detailed and comprehensive, encompassing a broad set of data that potential investors typically use during the screening process. However, different types of experts may have their own unique channels for gathering additional information, such as personal networks and specialized knowledge. A key distinction between VCs and technical experts is their access to different sets of private information and the varying weight they assign to this private information relative to public information in their evaluations. The second difference lies in how commonly observable information is processed. In our setting, both types of judges have access to the same standardized public information. However, financial experts interpret financial ratios or patent counts differently than technical experts. Moreover, their distinct skill sets lead to different ways of interpreting various pieces of information.

Consequently, the differences in evaluations between the two types of experts stem from two sources: unique private information and distinct methods of processing commonly observable information. Formally, we decompose a judge's evaluation score using Equation (1):

$$\text{Score}_{i,t,\mathbf{p}} = f(X_i) + \mu_{t,\mathbf{p}} + \varepsilon_{i,t,\mathbf{p}} \quad (1)$$

where i denotes the participant venture, t is the competition year, and p represents a set of group identifiers: industry and VC judge panel. $f(X_i)$ describes the relationship between the score $\text{Score}_{i,t,p}$ and the rich set of application information X_i for participant i. Different functional forms indicate varying methods of processing this 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. $\mu_{t,p}$ represents fixed effects corresponding to the competition year, industry and VC judge panel.

This decomposition allows us to split the judge score into two parts. $f(X_i)$ is the *common* perception of a participant 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, $\varepsilon_{i,t,p}$, captures the judge's individual evaluation based on private information. While $\mu_{t,p}$ accounts for factors that are not specific to startups and explains a significant portion of score variation, it is not the focus of our analysis.

We conduct the score decomposition separately for the two different types of judges (i.e., VC judges and scientist or technical judges), and denote Equation (1) for each as follows:

$$\text{Score}_{i,t,p}^{VC} = f^{VC}(X_i) + \mu_{t,p}^{VC} + \varepsilon_{i,t,p}^{VC}$$

$$\text{Score}_{i,t,p}^{Tech} = f^{Tech}(X_i) + \mu_{t,p}^{Tech} + \varepsilon_{i,t,p}^{Tech}$$

We conduct the following analyses to understand the differences between the two groups' evaluation methods. First, to test if both groups process hard information in the same way, we examine whether they have the same coefficients on a given characteristic x_i under the same specification of $f(.)$. Second, an auxiliary way to measure the extent of differences in processing common information is to calculate the correlation coefficient between the predicted scores $\hat{f}^{VC}(X_i)$ and $\hat{f}^{Tech}(X_i)$. A smaller correlation coefficient suggests greater divergence in evaluations due to differences in public information processing techniques. Third, we assess whether the two types of judges have different private information sets by examining the correlation between $\hat{\varepsilon}_{i,t,p}^{VC}$ and $\hat{\varepsilon}_{i,t,p}^{Tech}$. A correlation close to zero suggests private information sets of two judge types are likely independent. Last, comparing the adjusted R-squared values reveals which group of judges relies more on private information. If the adjusted R-squared for VC judges' score decomposition is larger (smaller), it indicates that VC judges rely less (more) on private information.

4.2 Evaluation and Venture Performance

We examine the relationship between judge evaluations and post-competition performances of participant startups. Both groups of judges may have the ability to identify startups with high innovation potential. Given the rising trend of recruiting STEM experts in the VC industry, we are particularly interested in whether scientist judges possess a superior ability over VC judges in screening high-quality startups. In addition, it is possible that neither

group's evaluations predict startups' post-competition performances, even if they have the ability to identify high-potential startups. On the one hand, judges may not truthfully express their opinions, either because providing the most accurate evaluation is costly and leads to careless scoring, or because they are incentivized to favor the competition organizers by consistently offering overly positive evaluations. On the other hand, the competition setting may introduce behavioral biases, as it differs from the judges' usual working environment.

To understand the predictability of judges' evaluations, we estimate the following regression model to examine the relationship between evaluation and post-competition performances. We evaluate venture performance across multiple dimensions, including innovation outputs, commercialization success, and the amount of VC funding received.

$$Y_{i,t,p} = \varphi \mathrm{Score}_{\mathrm{i,t,p}}^{\mathrm{Total}} + \mu_{\mathrm{t,p}} + e_{i,t,p}$$

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

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

$Y_{i,t,p}$ 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: industry and judge panel. We explore multiple specifications of the evaluation-performance relationship by gradually decomposing the independent variables from the total score to its four components, as outlined in the last line of equation (2): the predicted and residual scores from both VC and scientist judges. The first line in the regression only includes one key independent variable: the total score. An insignificant estimate of φ would suggests that the competition fails to identify participants with high potential. The specification listed in line 2 decomposes the total scores into two components: the VC judge score and the scientist judge score. The specification in the last line further decomposes these judge scores, as described in Section 4.1. This approach enables us to examine each component's role in predicting future performance. All key independent variables are normalized by dividing by their sample standard deviation, ensuring that the

coefficients can be interpreted as the effect of a one standard deviation change in the evaluation score on the outcome variable.

Regarding the outcome of receiving funding, if the post-competition investment decisions from the general VC industry align with judges' evaluations of startups during the competition, we would expect the evaluations to predict the startup's future fundraising success in the broader VC market.[12] Specifically, a significant relationship between VC judge evaluations and the likelihood of a venture receiving future funding suggests that VC judges' preferences are representative of the broader venture capital market. In the meantime, a positive association between the scientist score and future funding would indicate that VC investors take into account the perspectives of technical experts when making funding decisions.

4.3 VCs' Evaluation and Investment

We analyze how frequently the institutions that VC judges are affiliated with invest in the competing ventures. First, we assess whether the evaluations from the competition can predict subsequent investments from VC judges' affiliated institutions. Next, we examine whether the investment decisions differ when the VC judge personally reviewed the startup during the competition. We form all potential pairs of VC judges and ventures as our analysis sample. Conceptually, investment could occur in each pair of investor-startup. The dependent variable equals one if the VC judge subsequently invests in a venture and zero otherwise. Only 53 out of the 3,205 competing ventures ultimately receive funding from one of the institutions that their VC judges are affiliated with. The frequency of a realized investments is even lower in the sample of all potential pairs of VC judges and ventures. To address this, we scale the dependent variable by dividing it by the unconditional sample average of the variable. The regression model is as follows:

$$Y_{i,t,p,m} = \beta \mathrm{Score}^{\mathrm{VC}}_{\mathrm{i,t,p}} + \gamma \mathrm{Score}^{\mathrm{Tech}}_{\mathrm{i,t,p}} + \mu_{i,t,p} + \theta_{t,m} + e_{i,t,p,m} \qquad (3)$$

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

Different from the model in (2), model (3) is conducted at 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 $\mu_{i,t,p}$. We also analyze the sensitivity of VC judges' investments to both the predicted and residual components of the evaluations.

We also explore whether VC judges' investment behavior differs between startups they personally evaluated and those they did not. The random matching between startups and judges ensures that this difference is quasi-exogenous. For a given investor, the most salient difference is that they possess more information about the startups they judged. Specifically, the additional information comes from their ability to infer the scientist judges' evaluations once the competition results are released.

There are other potential sources of extra information as well. First, by judging a startup, the investor gains detailed insight prior to conducting due diligence, should they decide to invest. However, this should not affect the sensitivity of the investment decision to the scores when other VC judges evaluate the startup. Second, there may be information spillover within the panel of VC judges assigned to a given startup, although this would not affect the VC judges' ability to discern the scientist judges' opinions.

Other non-informational factors that may cause VC judges to treat startups they evaluated differently from those they did not include attention bias and search costs. When considering investment opportunities, VC judges are more likely to focus on startups they have personally examined, as it saves them time and effort in conducting due diligence. However, these factors would simply increase the likelihood of VC judges investing in startups they evaluated, without necessarily influencing the relationship between investment decisions and the evaluation scores.

We conduct tests using the following regression model:

$$Y_{i,t,p,m} = [\beta_J 1(J_{i,m} = 1) + \beta_{NJ} 1(J_{i,m} = 0)]\text{Score}_{\text{i,t,p}}^{\text{VC}} +$$

$$[\gamma_J 1(J_{i,m}=1)+\gamma_{NJ}1(J_{i,m}=0)]\text{Score}_{\text{i,t,p}}^{\text{Tech}}+$$

$$\rho 1(J_{i,m}=1)+\mu_{i,t,p}+\theta_{t,m}+e_{i,t,p,m} \quad (4)$$

$J_{i,m}$ is an indicator that equals 1 if investor m judged firm i and 0 otherwise. For each component of the scores, there are two coefficients: one for startups the investor judged (indexed by J) and the other for startups the investor did not judge (indexed by NJ). We are interested in the investment-score sensitivities in both scenarios. According to the "incremental information" hypothesis, we expect that $\beta_{NJ} \neq \beta_J$ and $\gamma_{NJ} \neq \gamma_J$. In particular, we hypothesize that scientists' evaluations play no role in VC judges' investment decisions for startups they did not evaluate ($\gamma_{NJ}=0$). However, once VC judges can infer the scientists' evaluations (even though they are not publicly available), their investment decisions may reflect the scientists' scores ($\gamma_J > 0$). The coefficient ρ on the judging indicator measures the overall difference in investment between judged and non-judged startups. We also analyze VC judges' responses to both the predicted and residual components of the scores.

5. Differences in VC and Scientist Judge Evaluations

In this section, we show significant discrepancies in how scientist judges and VC judges evaluate early-stage startups. Figure 1 visually depicts this disparity, showing how VC judge scores diverge from scientist judge scores (as indicated by the blue squares). The fitted linear regressions (red dashed lines) indicate weak correlation between these two sets of scores in both the 2017 and 2018 competitions, with correlation coefficients of 0.244 and 0.258, respectively. This simple comparison between VC judge and scientist judge scores suggests potential divergences in the information utilized and the methodologies applied in their assessments of ventures.

5.1 Evaluation and Venture Characteristics

We estimate Equation (1) with a focus on book equity characteristics. The estimation results are presented in Table 4, with each panel corresponding to a different dependent variable: VC judge score, scientist judge score, and 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 variables.

The results suggest that higher equity raised is associated with higher VC scores. VC judges appear to favor 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 4 shows that although scientist judges also favor 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 4, we analyze the "total score", which is 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 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 4, we introduce higher-order terms for all venture characteristics. We extend this analysis by employing polynomials up to the 10^{th} power and plot the adjusted R-squares (goodness-of-fit) in Figure 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 5^{th} 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 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 weigh private information more heavily than scientists when evaluating the early-stage startups in the competition. Comparing the adjusted R-squares in Panels A and B of Table 4 (and in Figure 3) reveals a striking difference. Regressions for scientist judge scores have adjusted R-squares that are, on average, twice as large as those 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. In contrast, 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.

5.2 Are VC Judges' Scoring Aligned with their Investments?

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 5 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.

6. Judge Evaluation and Future Venture Performance

This section explores the implications of judge evaluations for the post-competition performances of start-ups. In Section 6.1, we analyze the predictability of various scores on a venture's long-term innovation outputs. Section 6.2 focuses on the impact of these scores on financing and commercialization outcomes. Finally, in Section 6.3, we assess whether the evaluations are linked to actual investments made by VC judges in the ventures they evaluate. In all analyses, we begin by estimating the baseline correlation between future venture outcomes and three scores: the total score, VC judge scores, and scientist judge scores. Next, we run a horse-race test by including both the VC and scientist judge scores to determine whether one dominates the other. In addition, to further explore which type of information is most important in predicting performance, we decompose each judge's score into its predicted and residual components, incorporating them into our regression models.

6.1 Judge Evaluation and Innovation Performance

Table 6 presents the long-term predictive power of judge scores on various innovation outcomes, including patent applications and citations, professional and technical certificates, software copyrights, awards for technological achievements. The data were collected through January 2024. For each outcome variable, we analyze both the extensive margin (i.e., whether the startup generated a positive number for each innovation outcome) and the intensive margin (measured by the logarithm of the outcome counts).

Panel A and B report results from examining patent outputs from contestant ventures. In panel A, for each of the three scores in consideration (i.e., the total score, VC judge scores, and scientist judge scores), we observe its positive and strong associations with the likelihood as well as the number of patent applications (columns (1) through (3) and columns (9) through (11)). Furthermore, both observable information and private information components of those scores significantly predict future patent applications, as suggested by the estimates in columns (5) through (7) and in columns (13) through (15). Notably, when including aggregate VC and scientist judge scores in a single regression, we find that both contribute to predicting future patent applications (columns (4) and (12)). However, the magnitudes of the estimate on the scientist judge scores are higher than those on the VC judge scores (i.e., 0.054 vs. 0.044 in column 4). Furthermore, for both types of judges, their predicted scores and residual scores are significantly related to the future patent output, underscoring the values of both observable and private information at the time of the evaluation. Panel B presents the results using a proxy for patent quality, namely patent citations. We consider all the forward citations received by patents filed a venture until the end of year 2023, and divide the citation count by the total number of patents granted in the same time window. Scientist scores significantly predict the likelihoods of receiving any citation as well as the total citation count (columns (3), (4), (11) and (12)). In comparison, VC judge scores fail to predict the patent citations received at both intensive and extensive margin, as suggested by the insignificant coefficients on the VC judge scores (columns (2), (4), (10), and (12)). When examining the predictability of the decomposed elements of the scores, we find that the VC judge's evaluation based on observable information and scientist judges' private information consistently show significant predictive power.

Beyond patents, we examine other types of innovation outcomes in Panels C through E of Table 6. In general, the results are qualitatively similar to those in Panel A. While both VC and scientist judge scores are positively and significantly related to the innovation outcomes in question, 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.

6.2 Judge Evaluation and Financing

We analyze how judge scores predict future funding and commercialization outcomes. Panel A of Table 7 examines the likelihood of securing VC investments as well as the number of VC deals obtained. The results show a positive association between judge evaluations and both the probability and number of VC investments. However, only VC judge scores show significant predictability for future VC funding; scientist judge scores do not significantly predict future VC financing (columns (4) and (12)). Additionally, the predicted component of VC judge scores is much more influential than the residual component, with the coefficient of the former being more than five times that of the latter (columns (6) and (14)).

Furthermore, we examine the trademarks acquired by startups after the competition. Trademarks are often viewed as indicators of product market performance and a firm's financing potential. Previous research by Block et. al. (2014) and Chemmanur et.al. (2020) has shown trademarks are associated with VC investments, IPO success, investor confidence, and improved post-IPO performance. Panel B of Table 7 shows that higher total scores and VC judge scores strongly predict a larger number of new trademarks acquired after the competition. In contrast, the scientist judge scores do not show robust significance (columns (3) and (11)). When both VC and scientist scores are included in the regression, the predictive power of VC scores for trademarks remains strong, while the predictability of the scientist scores is minimal (columns (4), (8), (12), and (16)).

Taken together the asymmetric findings in Table 6 and 7, we draw two conclusions. First, the results tied to VC judge scores likely reflect the broader VC industry's evaluation of startups,

as suggested by the strong predictability of VC judge scores on funding and commercialization outcomes in Table 7. Second, VCs in general (including the VC judges and the larger set of VCs actively investing in the market) do not share the same perspectives with scientist judges in evaluating ventures, despite scientist judges' predictability on future innovation outcomes as shown in Table 6.

6.3 Do VC Judges Invest in the Competing Ventures?

The limited predictive power of scientist judge scores for VC investments raises a compelling question: why does not the scientist judges' assessment translate into real-world investment decisions? To explore this, we focus on the fundraising outcomes of contestant startups *specifically from the VC judges*. Following the methodology of earlier analyses, we run regressions using different judge scores, based on equations (2) and (3).

The results are presented in Table 8. The results are shown in Table 8. A higher score from VC judges during the competition is consistently associated with a greater likelihood that a venture will later receive funding from the paired VC judge. Note that the paired judge may or may not be the VC assigned to evaluate the venture during the competition. In contrast, the scientist judge score is not significantly related to the likelihood for a venture to receive funding from a VC judge (columns (3) and (4)). These results suggest VC judges apply different evaluation criteria than scientist judges when assessing the competing ventures as potential investment targets after the competition.

We proceed to investigate the conditions under which scientist scores influence a VC judge's decision to invest in a venture. Specifically, we differentiate whether the paired VC judge was also the one who evaluated the venture during the competition by constructing two indicator variables, "Judged" and "Not Judged." By interacting each of these variables with different types of scores (total, VC, and scientist), we examine whether the effects of those scores change when paired VC was actually involved in evaluating the venture during the competition.

Table 9 reports the results. First, total and VC scores consistently predict subsequent fund raising, regardless of whether the judge directly reviewed the venture during the competition (columns (1) and (2)). This suggests that these scores capture the broad aspects of venture quality relevant to overall VC investment decisions. Interestingly, scientist judge scores' predictability, however, is conditional: scientist judge scores are positively and significantly related to investment by a VC in a venture only when the VC actually served as a judge for the same venture in the competition, and the predictability mainly comes from the residual part of the scientist judge score (columns (3), (4), (7) and (8)). Scientist judge score's predictive power weakens and becomes unstable for VC judge's investment in unreviewed ventures, suggesting that VCs do not fully incorporate the scientist judges' evaluations in these ventures.

One likely explanation for the findings from Tables 8 and 9 is as follows. VCs are able to "back out" scientist judges' evaluations only for ventures they have actually reviewed in the competition. They can do so by comparing scores they assigned to a focal venture with the competition outcome (determined by the total score). For ventures they did not review, however, VCs might rely more heavily on their own assessments. This suggests that VCs may face constraints in incorporating scientists' evaluations into their decisions for certain ventures, but they seem to value this information when it is directly available.

7. Conclusion

This study investigates the discrepancies between VC and tech-oriented evaluations of early-stage innovative ventures, highlighting their differing predictions for venture performance. Using administrative data from a prestigious startup competition in Shanghai, where both VCs and scientists serve as judges to select high-potential ventures for grants, we find that VCs and scientists employ distinct approaches in screening startups.

Our analysis suggests distinct approaches between VCs and scientist-judges in evaluating innovative start-ups. First, we find that VC judges generally exhibit lower sensitivity to observed characteristics compared to scientist judges. VC judges prioritize firm capitalization, current profits and losses, and place additional value on positive current expenses. In contrast,

while scientist judges also assign higher scores based on capitalization, they do not place significant emphasis on other financial metrics, aside from current expenses. Second, we show that both VC and scientist judges employ distinct, private information in their evaluations, beyond what observable characteristics can capture. In particular, scientist judges rely more on the observable information of ventures, while VCs incorporate more private information into their assessments. Lastly, the results suggest that VC judges likely employ more sophisticated methodologies than scientists when processing the application materials of startups.

Our survey-based analysis of VC judges further confirms that they evaluate ventures according to their own investment philosophy. Specifically, VC judges who prioritize certain venture characteristics during evaluation tend to have a higher proportion of their scores explained by observable venture attributes.

Furthermore, we demonstrate that the differences between VC and tech-oriented evaluations have significant implications for long-term venture performance. Scientists show advantages than VCs in predicting innovation performances of a venture. However, ventures receiving higher scores from scientist judges do not secure significantly more VC funding after the competition. Interestingly, we find that VC judges incorporate scientist judges' insights into their investment decisions only when they directly participate in the competition.

Our study emphasizes the value of technology-proficient human capital in improving the efficacy of screening high-potential start-ups. These findings contribute to the growing body of research highlighting the role of human capital diversity in venture capital. The influx of individuals with STEM backgrounds into the VC industry signifies a growing recognition of the value of technological expertise in evaluating innovative ventures. This research underscores the need for further exploration into how diverse perspectives can be effectively integrated into VC decision-making. By highlighting the differences between VC and scientist evaluations, we offer insights for enhancing early-stage venture selection and fostering a more robust, innovative entrepreneurial ecosystem.

References

Abuzov, R. (2019). Busy venture capitalists and investment performance. Available at SSRN 3353343.

Armstrong, C. S., Dávila, A., Foster, G., & Hand, J. R. (2007). Biases in multi-year management financial forecasts: Evidence from private venture-backed US companies. Review of Accounting Studies, 12, 183-215.

Baron, J.N., Hannan, M.T., 2002. Organizational blueprints for success in high-tech start-ups: lessons from the Stanford project on emerging companies. California Management Review, 44 (3), 8–36.

Beuselinck, C., Elfers, F., Gassen, J., & Pierk, J. (2023). Private firm accounting: the European reporting environment, data and research perspectives. Accounting and Business Research, 53(1), 38-82.

Block, J. H., De Vries, G., Schumann, J. H., & Sandner, P. (2014). Trademarks and venture capital valuation. Journal of Business Venturing, 29(4), 525-542.

Bonelli, Maxime, Data-driven Investors (November 13, 2022). Available at SSRN: https://ssrn.com/abstract=4362173 or http://dx.doi.org/10.2139/ssrn.4362173

Cassar, G. (2009). Financial statement and projection preparation in start-up ventures. The Accounting Review, 84(1), 27-51.

Chemmanur, T. J., Rajaiya, H., Tian, X., & Yu, Q. (2020, October). Trademarks in entrepreneurial firm success: Empirical evidence from venture backed private firms and initial public offerings. In PBCSF-NIFR Research Paper, Proceedings of Paris December 2020 Finance Meeting EUROFIDAI-ESSEC.

Davila, A., & Foster, G. (2007). Management control systems in early-stage startup companies. The Accounting Review, 82(4), 907-937.

Ewens, M., & Marx, M. (2018). Founder replacement and startup performance. The Review of Financial Studies, 31(4), 1532-1565.

Gompers, P., Lerner, J., 2001. The Money of Invention. Harvard Business School Press, Boston.

Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2008). Venture capital investment cycles: The impact of public markets. Journal of Financial Economics, 87 (1), 1-23.

Gompers, P. A., Mukharlyamov, V., & Xuan, Y. (2016). The cost of friendship. Journal of Financial Economics, 119(3), 626-644.

Gompers, P. A., Mukharlyamov, V., Weisburst, E., & Xuan, Y. (2022). Gender gaps in venture capital performance. Journal of Financial and Quantitative Analysis, 57(2), 485-513.

González-Uribe, J., & Leatherbee, M. (2018). The effects of business accelerators on venture performance: Evidence from start-up Chile. The Review of Financial Studies, 31(4), 1566-1603.

González-Uribe, J., & Reyes, S. (2021). Identifying and boosting "Gazelles": Evidence from business accelerators. Journal of Financial Economics, 139(1), 260-287.

Hellmann, T., Puri, M., 2002. Venture capital and the professionalization of start-up firms: empirical evidence. Journal of Finance, 57 (1), 169–197.

Howell, S. T. (2020). Reducing information frictions in venture capital: The role of new venture competitions. Journal of Financial Economics, 136(3), 676-694.

Howell, S. T., Lerner, J., Nanda, R., & Townsend, R. R. (2020). How resilient is venture-backed innovation? Evidence from four decades of US patenting (No. w27150). National Bureau of Economic Research.

Hochberg, Y. V., & Fehder, D. C. (2015). Accelerators and ecosystems. Science, 348(6240), 1202-1203.

Hsu, D. H. (2004). What do entrepreneurs pay for venture capital affiliation? Journal of Finance, 59(4), 1805-1844.

Kaplan, S. N., & Strömberg, P. (2001). Venture capitalists as principals: Contracting, screening, and monitoring. American Economic Review, 91(2), 426-430.

Kaplan, S.N., Strömberg, P.E., 2004. Characteristics, contracts, and actions: evidence from venture capitalist analyses. Journal of Finance. 59 (5), 2177–2210

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

Kerr, W. R., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. Journal of Economic Perspectives, 28(3), 25-48.

Knight FH. (1921). Risk, Uncertainty, and Profit. Boston, MA: Houghton Mifflin.

Kortum, S., & Lerner, J. (2001). Does venture capital spur innovation?. In Entrepreneurial inputs and outcomes: New studies of entrepreneurship in the United States (pp. 1-44). Emerald Group Publishing Limited.

Lerner, J. (1994). Venture capitalists and the decision to go public. Journal of Financial Economics, 35(3), 293-316.

Lerner, J., & Nanda, R. (2020). Venture capital's role in financing innovation: What we know and how much we still need to learn. Journal of Economic Perspectives, 34(3), 237-261.

Lerner, J., & Nanda, R. (2023). Venture capital and innovation. Handbook of the Economics of Corporate Finance: Private Equity and Entrepreneurial Finance, 77.

Li, X., Liu, T., & Taylor, L. A. (2023). Common ownership and innovation efficiency. Journal of Financial Economics, 147(3), 475-497.

Lyonnet, V., & Stern, L. H. (2022). Venture Capital (Mis) allocation in the Age of AI. Fisher College of Business Working Paper, (2022-03), 002.

Nahata, R. (2008). Venture capital reputation and investment performance. Journal of Financial Economics, 90(2), 127-151.

Sørensen, M., 2007. How smart is smart money? A two-sided matching model of venture capital. Journal of Finance. 62 (6), 2725–2762.

Yu, S. (2020). How do accelerators impact the performance of high-technology ventures? Management Science, 66(2), 530-552.

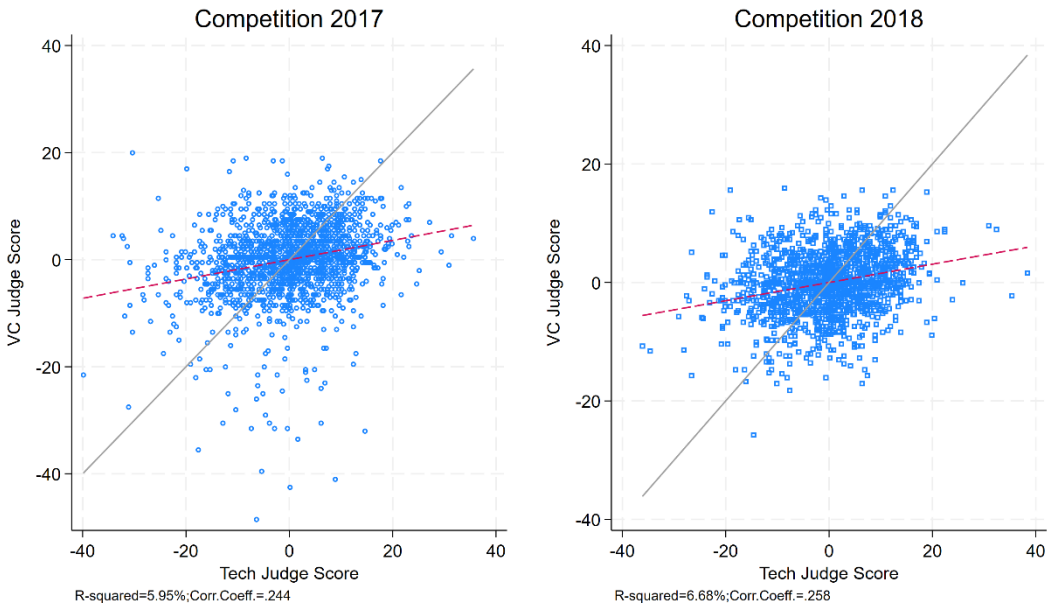


Figure 1. The Correlation Between Scores from VC and Scientist Judges

The figures illustrate the correlations between the scores assigned by VC and scientist judges during the 2017 and 2018 competitions. Each dot in the scatter plot represents an individual startup's evaluation. The solid line corresponds to the 45-degree reference line, while the dashed line represents the linear fit of the data. At the bottom of each figure, the R-squared value from the OLS regression of VC scores on scientist scores, along with the correlation coefficient between the two, is reported.

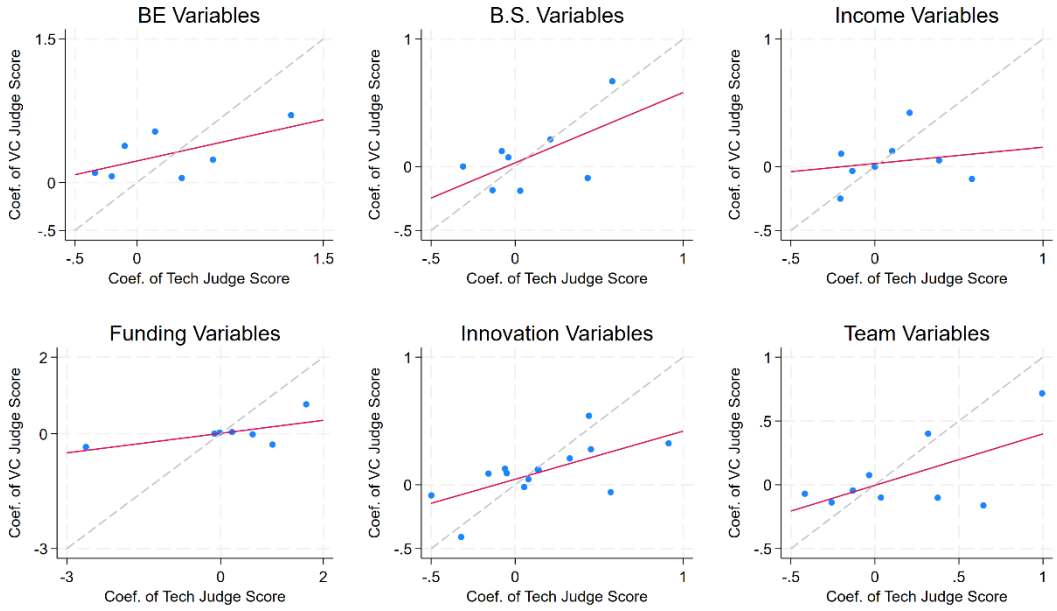
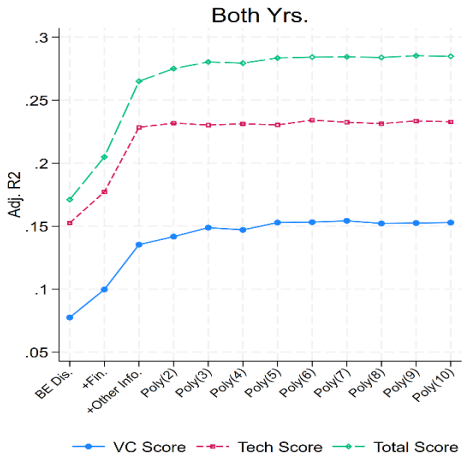
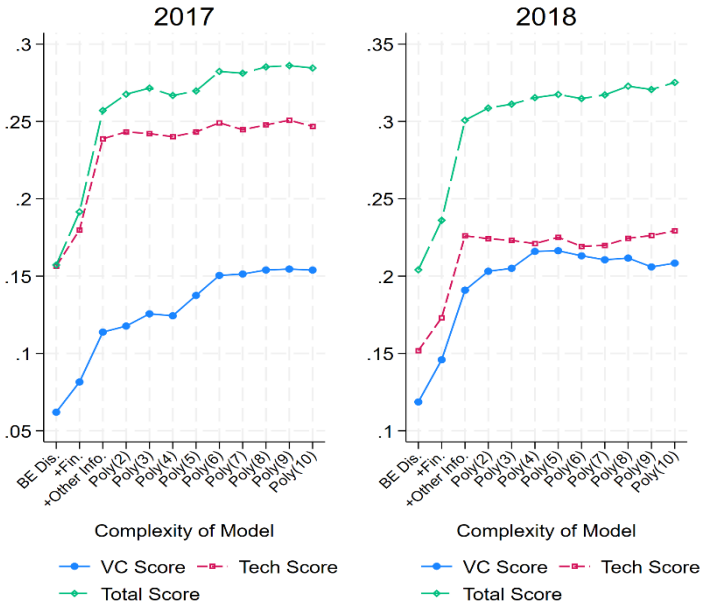


Figure 2. Comparison of Regressions Coefficients Using Different Scores as Dependent Variables

The figures display the differences between VC and scientist judge scores in relation to all observable characteristics. Regression coefficients for VC and scientist judge scores on these characteristics are derived from decomposition regression model (1), using a polynomial order of 10. For each characteristic, the two coefficients are plotted against one another. The characteristic variables are categorized into the following groups: book equity disaggregation ("BE" variables), balance sheet ("B.S." variables), income statement, project funding, current innovation performance, and the entrepreneurship team (see Section 3 and Table 1 for further details). In the plots, only the coefficients for the first order of each variable are shown.



Panel A: Full Sample



Panel B: Sub-sample by Competition Year

Figure 3. Fitness of Regression Models for Explaining Scores

The figures above illustrate how the adjusted R-squared of decomposition model (1) varies as the functional form of the regression becomes more complex. A total of 12 specifications are considered: the baseline specification includes only the book equity disaggregated variables; the second adds additional financial variables (balance sheet and income statement); the third incorporates all other characteristics; while the fourth through twelfth specifications progressively increase the polynomial order. Panel A shows results for the full sample, and Panel B presents results for the subsamples for the competitions in year 2017 and 2018. In each figure, three lines represent the results for three different dependent variables: VC judge score, scientist judge score, and total score.

Table 1. Summary Statistics: Application Information

This table summarizes key information from the application forms of competition participants. Panel A shows the breakdown of participant numbers by competition year and industry. The eight industries are defined by the competition organizer. Panel B classifies the data into six categories and reports the key summary statistics for all the variables in the sample. See Section 3.1 for detailed description of the variables. All the monetary-value variables are in CNY and are expressed in the units of 10,000.

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 CNY)							
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 CNY)							
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 CNY)							
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 Stock							
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. Survey Results from VC Judges

This table provides an overview of the survey results from VC judges. The upper section presents the number of VC judges contacted (along with the number of VC firms they represent) and the number of judges who responded (as well as the corresponding number of VC firms these respondents represent). The lower section summarizes the responses to the questionnaire. The two columns display the results for each competition year separately.

	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 3. Summary Statistics: Post-Competition Performance of Participant Start-ups

This table presents summary statistics for post-competition performance variables of the competition participants. The variables are grouped into three categories. The first category includes the number of funding deals and trademarks. The second category focuses on innovation activities, including patent applications (both total and excluding those filed after the first VC funding date if applicable), the firm-level percentage of applications granted, certificates for medical devices and drugs, software copyrights, and awards for scientific achievements (both national and regional). The third category pertains to credit risk, detailing the number of discredit enforcement cases and the corresponding cash amounts involved, as well as the number of court filings restricting high consumption and the associated cash amounts.

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
Patent Grant Rate	1448	80.0%	0.55	0.00	0.22	0.60	0.86	1.00
Patent Grant Rate (Before first VC Funding)	1341	79.2%	0.56	0.00	0.22	0.64	0.90	1.00
Certificate	3205	47.3%	2.56	0	0	0	3	28
Software Copyright	3205	54.3%	8.12	0	0	1	13	50
Award (All)	3205	43.5%	1.28	0	0	0	2	7
Award (National)	3205	42.0%	0.68	0	0	0	2	2
Award (Local)	3205	27.9%	0.60	0	0	0	1	5
Discredit Enforcement	3205	2.6%	0.10	0	0	0	0	2
Discredit Enforcement Cash Amount (CNY0000s)	3205	2.6%	9.97	0	0	0	0	63.4
Restriction of High Consumption	3205	3.9%	0.19	0	0	0	0	3
Restriction of High Consumption Cash Amount (CNY0000s)	3205	3.7%	30.70	0	0	0	0	396.7

Table 4. The Relevance of Accounting Information for Judge Scoring

This table presents the results of the score decomposition regression model (1). For brevity, only the first-order coefficients for the disaggregated book equity variables are shown, as these represent key accounting information related to the scores. All specifications include three sets of fixed effects: competition year, VC judge panel, and industry. The specifications differ in the included regressors and the polynomial order, which are indicated at the bottom of each panel. Both the R-squared and the within-group adjusted R-squared values for the fixed effects are reported. The table is divided into three panels, each corresponding to a different dependent variable: VC judge score, scientist judge score, and total score. Standard errors are clustered at the competition and industry levels, and t-statistics for the coefficients are 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

Table 5. Alignment between VC Judges' Scoring and Investments

This table shows which characteristics of VC judges are correlated with a greater reliance on application information for their evaluations. The dependent variable in the regressions is the absolute value of the residuals from the decomposition regression of VC judge scores. The first set of independent variables includes indicators of the VC judge's most relevant factors for investment provided in the survey. The second set pertains to the VC judges' backgrounds, while the third set focuses on the characteristics of the VC firms that the judge represents. Specifications (1)-(7) vary in the regressors included. 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.

Dep. Var.=Abs. Value of 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

Table 6. Do Scores Predict Long-Run Innovation Performance?

This table presents the results of the relationship between evaluations and innovation performance using regression model (2). Panels A through E feature different outcome variables. Specifications (1)-(8) transform the number of intellectual property rights or awards into binary indicators for non-zero values, while specifications (9)-(16) apply a logarithmic transformation (Log (y+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 for the coefficients are reported in the parentheses. * p < .10; ** p < .05; *** p < .01.

Panel A: Patent Applications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Depvar=1(Patent App.>0)								Depvar=ln(1+Patent App.)							
Total Score	0.077***								0.228***							
	(6.75)								(7.47)							
VC Judge Score		0.040***		0.044***						0.120***		0.131***				
		(4.12)		(4.50)						(4.35)		(4.76)				
Scientist Judge Score			0.051***	0.054***							0.150***	0.159***				
			(5.20)	(5.51)							(5.94)	(6.33)				
Predicted Total Score					0.024***								0.092***			
					(8.00)								(11.15)			
Residual Total Score					0.008***								0.016***			
					(3.88)								(2.96)			
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							0.159***	0.145***							0.595***	0.510***
							(7.96)	(6.51)							(11.04)	(8.27)
Residual Scientist Judge Score							0.018**	0.023**							0.025	0.039*
							(2.06)	(2.54)							(1.09)	(1.73)
Winner of Competition	0.056**	0.127***	0.111***	0.055**	0.047*	0.112***	0.092***	0.047*	0.236***	0.445***	0.399***	0.232***	0.194**	0.375***	0.321***	0.193**
	(2.08)	(5.43)	(4.62)	(2.03)	(1.74)	(4.70)	(3.84)	(1.72)	(3.08)	(6.66)	(5.80)	(3.04)	(2.57)	(5.61)	(4.75)	(2.57)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3205	3205	3205	3205	3203	3203	3203	3203	3205	3205	3205	3205	3203	3203	3203	3203
R-sq	0.1281	0.1205	0.1227	0.1283	0.1355	0.1250	0.1328	0.1368	0.1621	0.1532	0.1556	0.1623	0.1834	0.1667	0.1797	0.1850

Panel B: Average Number of Citations of Patent

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Depvar=1(Citations.>0)								Depvar=ln(1+Citations)							
Total Score	0.042**								0.043**							
	(2.17)								(2.32)							
VC Judge Score		0.005		0.010						0.008		0.012				
		(0.33)		(0.59)						(0.51)		(0.78)				
Scientist Judge Score			0.044***	0.045***							0.043**	0.044***				
			(2.68)	(2.72)							(2.56)	(2.61)				
Predicted Total Score					0.013***								0.013***			
					(2.99)								(3.02)			
Residual Total Score					0.004								0.004			
					(1.13)								(1.27)			
Predicted VC Judge Score						0.055**		0.052**						0.061***		0.065***
						(2.55)		(2.14)						(2.92)		(2.72)
Residual VC Judge Score						-0.012		-0.006						-0.011		-0.007
						(-0.77)		(-0.41)						(-0.75)		(-0.45)
Predicted Scientist Judge Score							0.074**	0.038							0.063**	0.019
							(2.40)	(1.08)							(2.00)	(0.52)
Residual Scientist Judge Score							0.031**	0.032**							0.032**	0.034**
							(2.06)	(2.14)							(2.12)	(2.24)
Winner of Competition	-0.015	0.040	-0.006	-0.018	-0.018	0.026	-0.010	-0.020	-0.060	-0.007	-0.048	-0.063	-0.063	-0.021	-0.051	-0.064
	(-0.37)	(1.17)	(-0.18)	(-0.45)	(-0.45)	(0.76)	(-0.30)	(-0.50)	(-1.48)	(-0.19)	(-1.38)	(-1.55)	(-1.56)	(-0.61)	(-1.43)	(-1.59)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1448	1448	1448	1448	1448	1448	1448	1448	1448	1448	1448	1448	1448	1448	1448	1448
R-sq	0.0253	0.0221	0.0269	0.0271	0.0279	0.0274	0.0275	0.0309	0.0204	0.0173	0.0214	0.0218	0.0226	0.0232	0.0217	0.0265

Panel C: Certificates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Depvar=1(Certificates>0)								Depvar=ln(1+Certificates)							
Total Score	0.084***								0.161***							
	(7.25)								(7.57)							
VC Judge Score		0.046***		0.050***						0.086***		0.093***				
		(4.53)		(4.92)						(4.48)		(4.90)				
Scientist Judge Score			0.054***	0.057***							0.105***	0.112***				
			(5.28)	(5.66)							(5.73)	(6.10)				
Predicted Total Score					0.031***								0.066***			
					(10.77)								(11.98)			
Residual Total Score					0.007***								0.011***			
					(3.32)								(2.80)			
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							0.226***	0.228***							0.471***	0.452***
							(11.36)	(10.10)							(12.65)	(10.66)
Residual Scientist Judge Score							0.006	0.010							0.005	0.013
							(0.65)	(1.09)							(0.30)	(0.79)
Winner of Competition	0.020	0.095***	0.082***	0.019	0.006	0.078***	0.052**	0.007	0.056	0.204***	0.173***	0.054	0.025	0.160***	0.109**	0.026
	(0.71)	(3.95)	(3.35)	(0.68)	(0.23)	(3.22)	(2.14)	(0.24)	(1.05)	(4.34)	(3.56)	(1.00)	(0.48)	(3.40)	(2.28)	(0.49)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3205	3205	3205	3205	3203	3203	3203	3203	3205	3205	3205	3205	3203	3203	3203	3203
R-sq	0.0854	0.0769	0.0783	0.0856	0.1016	0.0825	0.1053	0.1094	0.0987	0.0891	0.0914	0.0989	0.1243	0.1001	0.1277	0.1316

Panel D: Software Copyright

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Depvar=1(Software Copyrights>0)								Depvar=ln(1+Software Copyrights)							
Total Score	0.065***								0.189***							
	(5.66)								(6.31)							
VC Judge Score		0.035***		0.038***						0.084***		0.094***				
		(3.47)		(3.80)						(3.17)		(3.59)				
Scientist Judge Score			0.042***	0.045***							0.141***	0.148***				
			(4.09)	(4.41)							(5.22)	(5.50)				
Predicted Total Score					0.023***								0.064***			
					(7.86)								(8.10)			
Residual Total Score					0.006***								0.018***			
					(2.81)								(3.23)			
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							0.142***	0.118***							0.429***	0.388***
							(6.90)	(5.02)							(7.89)	(6.34)
Residual Scientist Judge Score							0.012	0.017*							0.053**	0.063**
							(1.36)	(1.85)							(2.16)	(2.56)
Winner of Competition	0.033	0.092***	0.081***	0.032	0.023	0.075***	0.063***	0.023	0.125*	0.316***	0.239***	0.119	0.099	0.272***	0.189***	0.095
	(1.24)	(3.94)	(3.43)	(1.21)	(0.88)	(3.17)	(2.67)	(0.87)	(1.67)	(4.79)	(3.54)	(1.59)	(1.32)	(4.08)	(2.80)	(1.27)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3205	3205	3205	3205	3203	3203	3203	3203	3205	3205	3205	3205	3203	3203	3203	3203
R-sq	0.0896	0.0844	0.0854	0.0897	0.0977	0.0904	0.0944	0.0981	0.1123	0.1053	0.1096	0.1129	0.1201	0.1104	0.1191	0.1215

Panel E: Awards for Technological Achievements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Depvar=1(Awards>0)								Depvar=ln(1+Awards)							
Total Score	0.092***								0.131***							
	(8.29)								(8.21)							
VC Judge Score		0.046***		0.050***						0.064***		0.070***				
		(4.59)		(5.09)						(4.27)		(4.74)				
Tech Judge Score			0.064***	0.067***							0.091***	0.097***				
			(6.51)	(6.96)							(6.94)	(7.42)				
Predicted Total Score					0.035***								0.054***			
					(12.41)								(13.21)			
Residual Total Score					0.007***								0.009***			
					(3.63)								(2.95)			
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 Tech Judge Score							0.237***	0.217***							0.363***	0.317***
							(12.45)	(9.84)							(13.44)	(10.08)
Residual Tech Judge Score							0.014	0.019**							0.015	0.023*
							(1.62)	(2.20)							(1.28)	(1.93)
Winner of Competition	0.055**	0.143***	0.117***	0.053*	0.040	0.119***	0.087***	0.039	0.130***	0.257***	0.217***	0.127***	0.105***	0.215***	0.170***	0.104***
	(2.01)	(5.95)	(4.78)	(1.94)	(1.47)	(4.92)	(3.59)	(1.44)	(3.27)	(7.23)	(6.09)	(3.21)	(2.69)	(6.07)	(4.86)	(2.67)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3205	3205	3205	3205	3203	3203	3203	3203	3205	3205	3205	3205	3203	3203	3203	3203
R-sq	0.1093	0.0976	0.1024	0.1098	0.1307	0.1094	0.1296	0.1343	0.1292	0.1170	0.1223	0.1298	0.1591	0.1352	0.1564	0.1621

Table 7. Do Scores Predict Future Fundraising & Commercialization?

This table presents the results of the relationship between evaluations and fundraising/commercialization using regression model (2). Panels A and B feature different outcome variables. Specifications (1)-(8) transform the number of VC funding deals or trademarks into binary indicators for non-zero values, while specifications (9)-(16) 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, 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)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Depvar=1(VC Deals>0)								Depvar=ln(1+VC Deals)							
Total Score	0.043***								0.055***							
	(6.47)								(6.16)							
VC Judge Score		0.045***		0.046***						0.057***		0.058***				
		(6.70)		(6.84)						(6.11)		(6.23)				
Scientist Judge Score			0.003	0.006							0.005	0.009				
			(0.46)	(1.00)							(0.59)	(1.16)				
Predicted Total Score					0.015***								0.020***			
					(7.33)								(7.18)			
Residual Total Score					0.004***								0.005***			
					(3.27)								(3.03)			
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							0.038***	-0.021							0.051***	-0.028
							(2.79)	(-1.28)							(2.93)	(-1.31)
Residual Scientist Judge Score							-0.006	0.002							-0.007	0.003
							(-0.92)	(0.30)							(-0.94)	(0.39)
Winner of Competition	0.052***	0.065***	0.114***	0.056***	0.045**	0.046**	0.108***	0.049**	0.058**	0.075***	0.137***	0.063**	0.050**	0.051**	0.128***	0.055**
	(2.63)	(3.62)	(6.15)	(2.84)	(2.30)	(2.55)	(5.78)	(2.53)	(2.34)	(3.43)	(5.77)	(2.55)	(2.01)	(2.31)	(5.43)	(2.24)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3205	3205	3205	3205	3203	3203	3203	3203	3205	3205	3205	3205	3203	3203	3203	3203
R-sq	0.0705	0.0756	0.0615	0.0759	0.0788	0.0921	0.0643	0.0927	0.0701	0.0752	0.0602	0.0756	0.0802	0.0954	0.0636	0.0961

Panel B: Trademarks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Depvar=1(Trademarks>0)								Depvar=ln(1+Trademarks)							
Total Score	0.021*								0.125***							
	(1.72)								(4.02)							
VC Judge Score		0.033***		0.032***						0.133***		0.134***				
		(3.12)		(3.06)						(4.63)		(4.67)				
Scientist Judge Score			-0.011	-0.008							0.007	0.017				
			(-1.01)	(-0.78)							(0.27)	(0.64)				
Predicted Total Score					0.007**								0.049***			
					(2.37)								(5.88)			
Residual Total Score					0.002								0.010*			
					(0.84)								(1.66)			
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							0.014	-0.009							0.150***	-0.022
							(0.68)	(-0.38)							(2.73)	(-0.35)
Residual Scientist Judge Score							-0.015	-0.011							-0.027	-0.006
							(-1.58)	(-1.11)							(-1.12)	(-0.24)
Winner of Competition	0.067**	0.061**	0.113***	0.072**	0.064**	0.053**	0.108***	0.068**	0.167**	0.203***	0.351***	0.180**	0.145*	0.145**	0.324***	0.157**
	(2.38)	(2.48)	(4.52)	(2.53)	(2.26)	(2.14)	(4.28)	(2.40)	(2.22)	(3.09)	(5.17)	(2.39)	(1.93)	(2.18)	(4.78)	(2.09)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3205	3205	3205	3205	3203	3203	3203	3203	3205	3205	3205	3205	3203	3203	3203	3203
R-sq	0.0302	0.0325	0.0296	0.0327	0.0310	0.0335	0.0303	0.0339	0.0514	0.0543	0.0464	0.0544	0.0580	0.0649	0.0495	0.0649

Table 8. Evaluation and VC Judges' Investments in Competing Ventures

This table presents the results of the relationship between evaluations and investment decisions by VC investors who acted as judges in the competitions, using regression model (3). The dataset for this regression 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 indicates whether the investor made an investment in the startup. The investment variable is normalized by dividing by the unconditional mean. In addition to fixed effects for competition year, VC judge panel, and industry, all specifications include competition-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)	(5)	(6)	(7)	(8)
Depvar= Normalized Investment								
Total Score	0.382**							
	(2.33)							
VC Judge Score		0.475***		0.474***				
		(3.42)		(3.41)				
Scientist Judge Score			-0.053	-0.017				
			(-0.37)	(-0.12)				
Predicted Total Score					0.127***			
					(3.04)			
Residual Total Score					0.038			
					(1.25)			
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							0.016	-0.737**
							(0.05)	(-2.25)
Residual Scientist Judge Score							-0.061	0.025
							(-0.47)	(0.19)
Winner of Competition	1.238***	1.269***	1.892***	1.292***	1.189***	1.071***	1.878***	1.235***
	(3.26)	(3.88)	(5.61)	(3.39)	(3.12)	(3.23)	(5.52)	(3.24)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects (Competition Year- VC Firm)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	334324	334324	334324	334324	334124	334124	334124	334124
R-sq	0.0018	0.0018	0.0018	0.0018	0.0018	0.0019	0.0018	0.0019

Table 9. When do VC Judges Invest in the Competing Ventures?

This table examines whether the relationship between evaluations and investment decisions by VC judges differs between startups they evaluated and those they did not. See regression model (4) for more details. The dataset for this regression 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, which indicates whether the investor made an investment in the startup, is normalized by dividing it by its unconditional mean. All specifications include fixed effects for competition year, VC judge panel, and industry, as well as competition-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)	(5)	(6)	(7)	(8)
Dep. Var.= Normalized Investment								
Total Score*Judged	3.270***							
	(3.79)							
Total Score*Not Judged	0.297*							
	(1.79)							
VC Judge Score*Judged		2.374***		2.295***				
		(3.06)		(2.95)				
VC Judge Score*Not Judged		0.418***		0.420***				
		(2.98)		(2.98)				
Scientist Judge Score *Judged			1.863**	1.817**				
			(2.33)	(2.27)				
Scientist Judge Score *Not Judged			-0.109	-0.070				
			(-0.74)	(-0.48)				
Predicted Total Score*Judged					0.168			
					(1.53)			
Predicted Total Score*Not Judged					0.126***			
					(3.00)			
Residual Total Score*Judged					0.377**			
					(2.31)			
Residual Total Score*Not Judged					0.028			
					(0.92)			
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							-0.368	-5.853***
							(-0.48)	(-4.22)
Predicted Scientist Judge Score *Not Judged							0.028	-0.585*
							(0.10)	(-1.78)
Residual Scientist Judge Score *Judged							1.728**	1.901***
							(2.34)	(2.58)
Residual Scientist Judge Score *Not Judged							-0.114	-0.030
							(-0.86)	(-0.22)
Winner of Competition * Judged	2.427	4.053***	4.498***	2.477	4.217***	4.724***	5.332***	3.910***
	(1.49)	(2.77)	(2.99)	(1.52)	(2.82)	(3.33)	(3.75)	(2.62)
Winner of Competition * Not Judged	1.204***	1.188***	1.816***	1.258***	1.100***	0.964***	1.777***	1.157***
	(3.14)	(3.60)	(5.34)	(3.28)	(2.87)	(2.89)	(5.19)	(3.02)
Fixed Effects (Competition Year, VC Judge Panel, Industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects (Competition Year-VC Firm)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	334324	334324	334324	334324	334124	334124	334124	334124
R-sq	0.0019	0.0019	0.0018	0.0019	0.0019	0.0019	0.0018	0.0020

Appendix A. Technology Human Capital in the VC Industry

One significant motivation of this paper is the observation of a growing number of individuals joining the VC profession with PhD qualifications, especially in the STEM fields. To illustrate, using the data from Pitchbook, we identify individual investors worldwide who are affiliated with at least one VC deal and also hold a doctoral degree in the fields of STEM. The calculation considers active investors worldwide from 2007 to 2015 for whom Pitchbook provides educational background information (i.e., degree types and fields of study). 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), success is defined as either an IPO or a high-value acquisition (with at least twice the amount of total investment received) of the portfolio company.

The share of investors with a doctoral degree in STEM among all the active VC investors is about 8% from 2007 to 2015. Nevertheless, investors with a PhD in STEM significantly outperform their peers. By tracking the exit status of their portfolio companies up to March 2022, we find that investors with a PhD in STEM achieve a rate of 20% in bringing their portfolio companies to a high-status exit through either an IPO or a high-valuation acquisition. This success rate is significantly higher than the rates among investors without any degrees in STEM or having a degree in STEM at bachelor or master levels (i.e., both groups having a success rate of 12%). Furthermore, zooming into the development stages and industry sectors of portfolio companies, we find such superior performances of STEM PhD-investors are driven by their success in early-stage ventures and technology-intensive sectors (see Figure A1 (c) & (d)). We also confirm that the advantages of STEM PhD-investors cannot be purely attributed to their high overall level of human capital acquired through advanced education, as their success rates remain significantly higher than those of the investors with a doctoral degree in non-STEM fields (see Figure A1(b)).

These compelling observations highlight the valuable skills and expertise of investors who have received advanced training in the STEM fields. We are motivated to understand the advantages of the STEM-PhD investors in screening an entrepreneurial project at an early stage, and the Startup in Shanghai competition provides a suitable setting for our objectives.

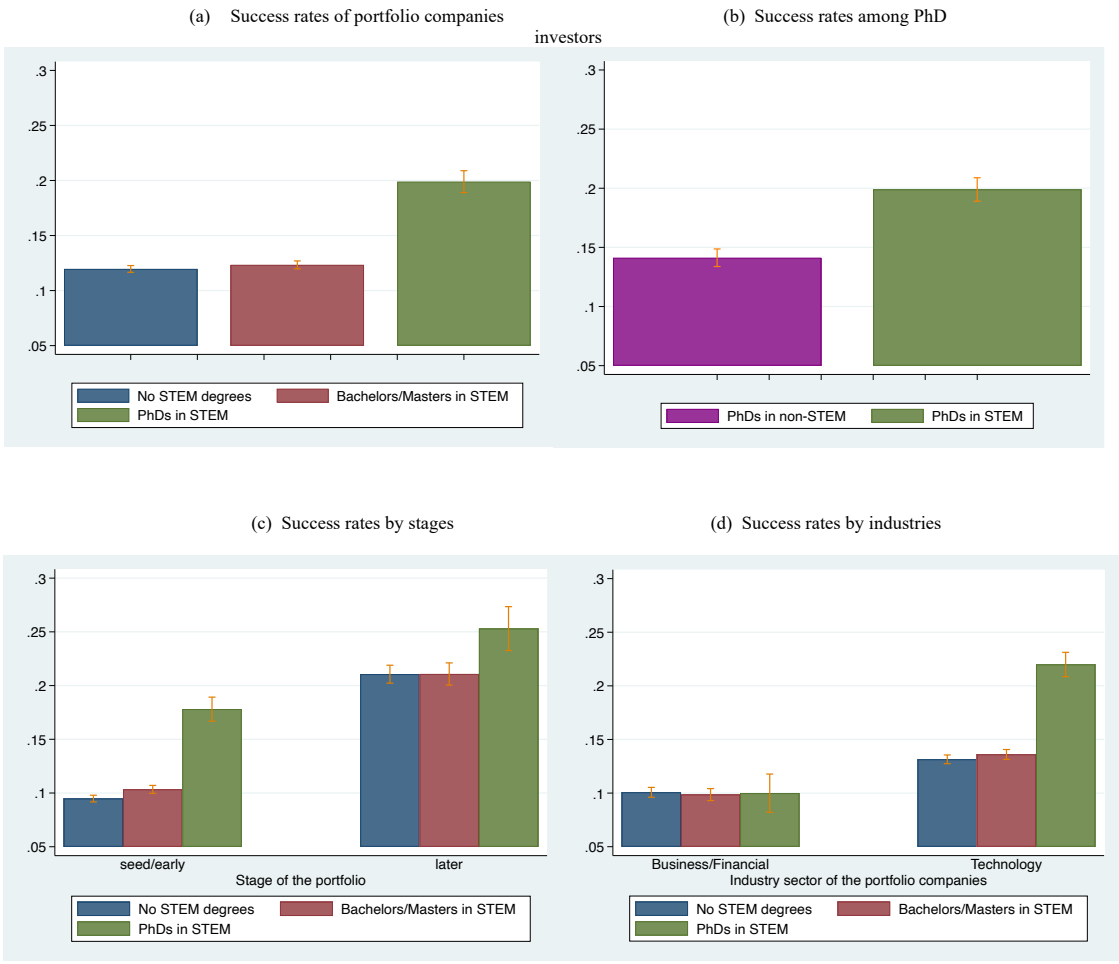


Figure A1: Success Rates of Portfolio Companies by Investor Education Backgrounds

This figure plots the success rates of portfolio companies that received VC funding from 2007 to 2015 worldwide by the educational backgrounds of their affiliated VC investors. We extract the data from Pitchbook and consider 33,167 distinct portfolio companies affiliated with 22,624 investors for whom education information is available (i.e., degree types and fields of study). We track the exit status of a portfolio company up to March of 2022, allowing for at least six years for development for a venture. Consistent with the literature (Ewens and Marx, 2018), a success is defined as either an IPO or a high-value acquisition (with at least twice the amount of total investment received) of the portfolio company. Panel (c) records the development stage of a venture when it first received funding from a focal investor. The classification of STEM degrees is according to STEM designated degree program list provided by the U.S. Department of Homeland Security, but we have excluded STEM degrees received in the fields of social sciences (i.e., economics and psychology). Panel (d) divides portfolio companies by their industry sectors according to the classification by Pitchbook. There are 7 distinct industry sectors in Pitchbook, namely Business Products and Services (B2B), Consumer Products and Services (B2C), Financial Services, Information Technology, Healthcare, Materials and Resources, and Energy. We count a portfolio company in the industry group of Business/Financial if their industry sector is one of the following: B2B, B2C, and Financial Services. Otherwise, a portfolio company is categorized into the technology group.

Appendix B. 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.