Technology Literacy and Deep-Tech Investment: Evidence from VC Industry*

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Abstract

This paper examines how the technology literacy of venture capital (VC) firms influences investment in deep-tech startups. Using novel matched data from PitchBook and Revelio Labs, we show that tech-literate VCs, proxied by the share of Ph.D.-trained partners, are scarce, geographically concentrated, and more likely to fund deep-tech ventures. Startups backed by these VCs experience lower failure rates and higher IPO probabilities. Based on these findings, we develop and calibrate a dynamic matching model with hiring frictions for Ph.D.-trained partners. The model reveals that lowering the cost for Ph.D.s to become VC partners does not necessarily raise their equilibrium share, providing a potential explanation for the persistently low and recently declining presence of Ph.D. partners in the industry.

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1 Introduction

Venture capital (VC) has long been a critical source of financing for high-growth startups, particularly in information technology and software. However, recent research suggests that VC funding is becoming increasingly concentrated in a narrow set of innovations (Lerner and Nanda, 2020; Gompers, Gornall, Kaplan, and Strebulaev, 2020). This trend raises concerns about the allocation of capital in an era marked by rapid technological progress, where breakthrough scientific discoveries require substantial funding to be commercialized.

A key friction in the financing of deep-tech ventures lies in the knowledge gap between investors and entrepreneurs. While traditional VCs are typically trained in business or finance, evaluating deep technologies often requires domain-specific expertise. Investors without sufficient technical literacy may underestimate or misinterpret the commercial potential of scientific innovations, leading to systematic underinvestment. Alternatively, they may misallocate capital to superficially impressive but technically flawed ventures, especially in sectors where technological validation is difficult for outsiders to assess. This knowledge asymmetry raises questions about the efficiency of capital allocation in frontier innovation markets.

In this paper, we argue that technology literacy within VC firms is a critical determinant of funding deep-tech startups. We begin by documenting three sets of stylized facts and then develop a structural model to explain these patterns. First, we show that the supply of tech-literate VCs is limited, resulting in a structurally tight market for deep-tech capital. Using a new dataset that links VC investment records from PitchBook with workforce and job posting data from Revelio Labs, we find that the proportion of VC firm partners with PhD-level training—a proxy for technology literacy—is both low and declining. This limited supply of tech-literate VCs creates a funding bottleneck. The tightness is not uniform: it varies significantly across geographies. While California, for example, accounts for 26% of all deep-tech startups in the United States, only 10% of VC firms operating in the state have at least one PhD-trained partner. This geographic asymmetry in supply and demand introduces substantial frictions in the matching process between startups and suitable capital providers, leading to spatially heterogeneous funding outcomes for innovation.

Second, we examine the role of investor technology literacy in investment choices. Using a matched sample of realized and counterfactual VC-startup pairs, we find that VC firms with higher PhD partner ratios are significantly more likely to invest in deep-tech startups. A 10% increase in the PhD partner ratio increases the likelihood of investment in a deep-tech firm by 3.3%, relative to a baseline investment probability of approximately 2%. These results suggest that more tech-literate VCs are more willing to invest in deep-tech ventures. To validate these findings, we further employ an instrumental variable approach and obtain consistent results, reinforcing the robustness of the relationship between VC technology literacy and investment in deep-tech startups.

Third, we test the consequences of these investments. Deep-tech startups backed by more technologically literate VCs experience better performance outcomes. Specifically, we find that a 10% increase in the PhD partner ratio reduces the failure rate of deep-tech startups by 6.4% and increases the IPO probability by 19.0%. The evidence implies that investor expertise is not merely correlated with investment selection but also contributes to the long-run success of funded ventures. Tech-literate VCs may have better screening ability, provide more valuable guidance, better strategic oversight, or access to technical networks that facilitate commercialization and exit.

To interpret these findings and assess their implications for capital allocation efficiency, we develop a dynamic structural model of VC–startup matching under directed search and market frictions, following the canonical framework of Gourio and Rudanko (2014). VC firms are heterogeneous in productivity and employ two types of labor: general staff to process investment deals, and technical specialists—modeled as PhD-trained partners—who search for and evaluate deep-tech startups. Hiring these specialists is costly and subject to convex adjustment costs, reflecting both labor market frictions and the limited supply of highly skilled technical talent.

In each period, VC firms compete to match startups and generate revenue from successful investments. Their operations are constrained by two primary dimensions. First, the supply side of capital—defined as a VC firm's capacity to make investments—is determined by an exogenous productivity shock and the firm's employment of regular workers who process deals. Second, the demand side for capital is limited by the number of deep-tech startups actively seeking funding. The VC revenue function captures the complementarity between capital demand and capital supply. Investment relationships are formed through a frictional matching process, in which the probability of matching depends on market tightness, which refers to the imbalance between the number of deep-tech startups seeking funding and the availability of tech-literate VC firms.

We quantitatively solve the model for steady-state equilibrium and calibrate it to match key empirical moments computed from the empirical sample. Specifically, the calibration targets include the average VC earnings-to-capital ratio, auto-correlation of earnings, the internal rate of return (IRR), the average growth rate of capital investment, the ratio of new investment to existing capital, the average ratio of PhD-trained partners to the number of startups, and the average share of wage expenditures allocated to PhD partners relative to total labor costs.

In the model, within a given economy, VCs differ in productivity and optimally choose their level of technical literacy (i.e., number of Ph.D. partners to hire). Cross-sectionally, more productive VCs find it optimal to invest more heavily in hiring PhD partners to screen for deep-tech opportunities. The model predicts that these firms will exhibit higher investment intensity and better performance, consistent with our empirical results. Moreover, the model implies that when market tightness is low (i.e., when the ratio of deep-tech startups to VC Ph.D. partners is high), VCs obtain higher returns due to improved bargaining power.

In the counterfactual analysis, we examine how equilibrium outcomes change across different economies by varying the entry cost of becoming a Ph.D. partner. We investigate the effect of the entry cost of being Ph.D. partners in the occupational choice of households on the equilibrium labor composition and overall VC investment return. The hump-shaped relationship between the equilibrium number of Ph.D. partners and the entry cost, together with the corresponding U-shaped pattern in VC aggregate IRR, suggests that lowering entry barriers for Ph.D. partners does not necessarily increase overall returns in the VC industry. When the cost of becoming a Ph.D. partner is high, the equilibrium number of Ph.D. partners remains limited, while the return to VC investment is relatively high because of higher bargaining power. Therefore, VC firms face little incentive to hire more Ph.D. partners, resulting in an equilibrium with a structurally low level of technology literacy among VCs.

This research contributes to three streams of literature. First, it adds to the body of work on financing innovation by highlighting how *human capital constraints* among investors shape the flow of capital to innovations. Prior studies highlight the role of staged financing and experimentation in supporting innovative ventures (Kerr and Nanda, 2015). While some evidence suggests that, in the context of grant funding, evaluators may penalize proposals that align too closely with their own expertise or exhibit high levels of novelty (Boudreau, Guinan, Lakhani, and Riedl, 2016), our findings indicate that this pattern does not extend to the venture capital setting. Instead, we show that technology literacy among VC investors enhances capital allocation to deep-tech startups, highlighting the importance of technology literacy in VC investments.

Second, our paper speaks to the literature on matching in the VC industry. Existing research has employed static matching models (Sørensen, 2007) and search-and-matching frameworks (Ewens, Gorbenko, and Korteweg, 2022) to characterize VC investment dynamics. We extend this literature by incorporating the hiring costs faced by VC firms, which influence the matching outcomes between VCs and startups. This paper provides new insights into how hiring frictions impact investment decisions, particularly in deep-tech sectors where both specialized expertise and recruitment challenges play a critical role in the allocation of capital. This paper is also among the first to incorporate a dynamic heterogeneous firm framework with a directed search model from labor economics into the VC literature.

Third, our paper contributes to the literature on VC investment decisions. Existing empirical research examines how VC teams operate and make investment decisions (Gompers et al., 2020), while theoretical work explores the rationale behind the champion voting rule employed by investment committees in early-stage VC investments (Malenko, Nanda, Rhodes-Kropf, and Sundaresan, 2024). Our study extends this literature by demonstrating how technology literacy among VCs influences investment decisions and improves capital allocation efficiency.

The rest of this paper is organized as follows. Section 2 provides an overview of the evolving role of technology literacy in VC investments. Section 3 describes the data sources and key measures used in our analysis. Section 4 presents the stylized facts. Section 5 introduces a dynamic matching model. Section 8 concludes.

2 Investment in Technology

The financing of innovation and technology entrepreneurship has been a central theme of the VC industry since its inception (Nicholas, 2019). Historically, early VC firms often had strong technical backgrounds, particularly in engineering and the sciences, enabling them to assess and commercialize frontier technologies emerging from government-funded research and universities.[1] These early-stage investments were characterized by high technical risk, as they often involved nascent technologies with uncertain commercial viability. However, as noted by Thomas J. Perkins, co-founder of Kleiner Perkins, in what became known as "Perkins's Law": Market risk is inversely proportional to technical risk. This suggests that firms capable of overcoming significant technical challenges face less competitive pressure, as the complexity of their innovations serves as a natural barrier to entry.

Despite this early emphasis on deep technological innovation, the contemporary VC landscape has shifted towards a greater focus on software and pharmaceutical investments. While

[1] For example, the early investments made by Fairchild-spinout VC firms played a crucial role in translating semiconductor research into commercial applications.

software startups still require technical expertise, their business models prioritize rapid iteration, agile development, and sales-driven expansion (Lerner and Nanda, 2020). The capital efficiency of software firms due to the ”spray and pray” approach (Ewens, Nanda, and Rhodes-Kropf, 2018), combined with their ability to scale quickly with minimal fixed costs, makes them particularly attractive to VCs seeking high-growth opportunities with relatively low upfront capital requirements. On the other hand, pharmaceutical ventures, despite being highly R&D-intensive, follow a well-defined regulatory and clinical trial pathway. The structured nature of drug development, coupled with an established acquisition market where large pharmaceutical firms actively acquire successful biotech startups (Cunningham, Ederer, and Ma, 2021), reduces some of the uncertainties associated with investment returns in this sector.

This transformation in the VC industry aligns with the evolving demographic and professional composition of venture investors. In contrast to the early days of VC, when many investors had deep technical expertise, today’s VC professionals are more likely to come from backgrounds in business administration (MBA) or finance. Consequently, VCs with limited technology literacy increasingly rely on advisory committees, technical consultants, and limited partners (LPs) with specialized domain expertise to guide their investment decisions. While these experts provide valuable technical insights, they do not hold decision-making authority. Instead, general partners (GPs), who typically come from business or finance backgrounds, make the final investment decisions, prioritizing commercial viability, market scalability, and exit potential over purely technological advancements. However, despite expert advice, GPs with limited technical expertise often struggle to accurately assess and value startups in highly sophisticated fields, such as quantum computing.

Although startups developing new technologies have the potential to generate significant value for investors and the broader market, the decline in technology literacy among VCs presents a critical challenge: the risk of underinvesting in groundbreaking innovations. During the screening process, VCs without deep technical expertise often face difficulties in evaluating the technological potential, scalability, and risks. Without the necessary expertise, the misjudgment can lead investors to favor more familiar business models with clearer pathways to profitability.

Beyond the initial investment decision, technology-literate VCs play a crucial role in the long-term success of deep-tech startups. Their understanding of technologies allows them to provide more practical advice on translating innovation into viable business models. These VCs contribute not only capital but also valuable insights, adding value to the startups after investments.

In the following section, we present empirical evidence that VCs with higher levels of technology literacy are more inclined to invest in deep-tech startups. Moreover, we demonstrate that startups invested by these VCs exhibit better performance in terms of exit outcome, reinforcing the importance of technological expertise in venture capital markets.

3 Data and Measures

3.1 Data

Startup and Investment Data We construct our dataset using PitchBook, a leading database on venture capital transactions that provides detailed information on financing rounds, investor characteristics, and firm performance metrics. It is owned by MorningStar, and has a growing prevalence in venture capital research studies as it has better data coverage of startup financing deals than other data sources. Our sample includes all U.S.-headquartered firms founded between 2000 and 2023[2], and then we retrieve all financing rounds associated with these firms. Since VCs frequently syndicate deals, each round may involve multiple investors. To ensure our analysis focuses on venture-backed transactions, we restrict our sample to deals where at least one investor belongs to the categories of Accelerator/Incubator, Venture Capital, Angel Group, or Angel (individual).

[2]PitchBook data as of February 2025.

Revelio Labs Data We obtain employer-employee matched data from Revelio Labs, which is underpinned by LinkedIn data. Revelio Labs is a workforce intelligence platform that tracks over 1.1 billion individuals' career trajectories, including educational background and professional networks. This dataset enables us to measure the presence of technology-literate partners within VC firms and their engagement with deep-tech startups. Our data consists of the universe of LinkedIn users, their CVs, and their employer profile pages up to July 2024.

We also obtain job posting data from Revelio Labs, which compiles a comprehensive dataset of over 2 billion job postings from 5.25 million companies. This data is sourced directly from 270,000 employer websites, major job boards, and leading staffing firm platforms. To ensure accuracy, Revelio Labs employs a deduplication algorithm that removes duplicate postings appearing across multiple job boards. A key advantage of this dataset is its rich level of detail, capturing information such as required skills, education levels, job responsibilities, and employer attributes. For our analysis, we focus on job postings located in the United States, ensuring that each entry has a non-missing employer identifier and a complete job description.

Linking Pitchbook and Revelio Labs We merge individual profile data from Revelio Labs with PitchBook using company information. The merging process is conducted sequentially, prioritizing company ticker numbers, company website URLs, LinkedIn URLs, and exact company name matches. Additionally, we integrate the job posting data from Revelio Labs using a unique company identifier assigned by Revelio Labs.

After merging, 82% of U.S. startups in PitchBook are linked to Revelio Labs data, and 52% of these startups have at least one job posting merged. To ensure data relevance, we restrict our sample to VC firms where at least one partner has data available in the Revelio individual profile dataset and to startups that have at least one recorded job posting.

One potential limitation of restricting the analysis to firms with job postings is the substantial reduction in sample size, as nearly half of the firms are excluded. To assess potential selection bias, we conduct a balance test comparing firms with and without job postings, as reported in Table A.1. The composition of the founding team and the year of establishment are largely similar across the two groups. However, firms with job postings tend to have raised significantly more capital, which aligns with the expectation that startups typically begin hiring following a round of financing. By focusing on firms that have posted job openings, our sample captures firms that are relatively more successful, as they are actively expanding their workforce and advancing their business operations. As a result, our analysis primarily applies to more mature startups.

3.2 Key Measures

Technology Literacy Our VC-year level technology literacy measure is constructed based on the partner education composition of venture capital firms. A partner is defined broadly to include any individual with a job title containing "partner", "founder", "angel", "owner", "advisory board member", or "executive".

We begin by identifying the highest level of education attained by each VC partner and determining whether they hold a PhD degree. Next, we link VC partners to their employment histories, recording their start and end dates at each firm. We then aggregate the total number of partners and the number of partners with a PhD at the VC firm-year level. If a partner exits the VC firm, they are excluded from the calculations following their departure year. To quantify a VC firm's technology literacy in a given year, we use the ratio of partners holding a PhD degree, providing a measure of the firm's expertise in deep technology investments.

Deep-Tech Startups A challenge in this research is identifying deep-tech startups. Inspired by the approach of Babina, Fedyk, He, and Hodson (2024), we leverage job posting data from Revelio Labs and classify deep-tech startups as companies that require a PhD or

MD (hereafter referred to as PhD) degree for their positions. This serves as a useful proxy because deep-tech startups typically operate in highly specialized fields such as artificial intelligence, biotechnology, and quantum computing, where advanced research expertise is essential. Requiring a PhD in job postings reflects the firm's need for cutting-edge technical knowledge, making it a reasonable indicator of deep technology startups. We define a startup as "isDeepTech" if at least one of its job postings requires a PhD degree. Based on this criterion, 16% of the sample is identified as deep-tech startups.

The final sample of analysis includes 42,412 startups and 11,854 VCs. The regression is at the VC-startup-deal level with a sample size of 262,455. Table 1 presents the summary statistics for key variables used in the analysis, with the observation level at the VC-startup-deal level. The majority of VC firms in the deals do not have any PhD partners, with an average PhD partner ratio of 7.81%, indicating that high technology literacy is relatively uncommon among VC firms. In the sample, 30.6% of VC deals involving deep-tech startups are classified as deep-tech. [3] Regarding exit performance, 5.74% of startups in the deal fail or go bankrupt. Meanwhile, 17.43% of startups in the deal exit through mergers or acquisitions (M&A), and 4.81% successfully go public.

4 Stylized Facts

4.1 Fact 1: Limited supply of tech-literate VCs and geographic variation in market tightness in deep-tech funding

We begin our empirical analysis by documenting the structural tightness in the market for deep-tech capital. The number of tech-literate VCs remains limited and has declined over time. This persistent scarcity contributes to market tightness, which refers to the imbalance between the demand for funding from deep-tech startups and the supply of tech-literate VC

[3] At the startup level, 18.9% of firms are classified as deep-tech, whereas at the VC-deal level, 30.6% of deals involve deep-tech startups.

firms. Moreover, the shortage is not evenly distributed across regions, resulting in substantial geographic variation in access to tech-literate venture capital.

The summary statistics in Table 1 highlight the low ratio of PhD partners in VC firms. Figure 1 further supports this observation. The green line represents the industry-wide share of PhD partners among all VC partners, while the blue line shows the average PhD ratio at the firm level. Both lines show a similar trend: The share of PhD partners has a noticeable decline since 2010, indicating an increasing scarcity of PhD partners in the industry. This downward trend suggests that, despite the growing importance of deep-tech investments, the supply of VCs with strong technical backgrounds is not keeping pace with industry needs. As a result, deep-tech startups may face challenges in securing investment from tech-literate VCs who can provide not only capital but also the strategic guidance necessary for commercializing complex technologies.

The low ratio of PhD partners suggests that hiring PhD-trained professionals in the VC industry can be costly and challenging. First, junior positions in VC firms are predominantly occupied by individuals with backgrounds in finance and management. As a result, fewer PhD-trained professionals enter the industry at early career stages, limiting the pipeline of candidates who can advance to partner positions. Table A.2 provides insights into the educational background of individuals working in the VC industry, along with the proportion of PhD holders in each major field. The majority of VC professionals hold degrees in Business, yet only 0.78% of them have a PhD. While Biology exhibits the highest PhD ratio, it represents only a small fraction of the overall VC workforce, further underscoring the limited presence of PhD-trained professionals in the industry.

Second, lateral hiring from other VC firms is constrained by the already low supply of PhD partners. Table A.3 reports the major fields of study for VC partners, categorized by their highest degree obtained. The data show that most VC partners hold Bachelor's or Master's degrees, with fewer than 200 partners holding a PhD in each field. This scarcity of PhD-trained partners makes it difficult for firms to recruit from competitors or expand their tech-literate leadership through external hiring.

Beyond the scarce supply of tech-literate VCs, the geographic distribution of deep-tech startups and PhD-backed VCs further contributes to the variation in market tightness between deep-tech firms and tech-literate VCs. Table 2 presents the proportion of deep-tech startups and the share of VC firms with at least one PhD partner across states with the highest number of deep-tech startups. As shown in the table, while California has highest number of deep-tech startups and the second-highest share of deep-tech startups at 26%, the proportion of VCs with a PhD is among the lowest, at only 10%. This imbalance suggests that deep-tech startups in California may face greater challenges in securing funding from tech-literate VCs compared to those in Massachusetts and New York, where the concentration of PhD-backed VCs is higher.

Figure 2 further illustrates this geographic misalignment by mapping the ratio of deep-tech startups and the proportion of VCs with PhD partners across different states. The figure reinforces the finding that the distribution of deep-tech startups does not fully align with the availability of tech-literate VCs. While California has a relatively high concentration of deep-tech startups, it does not exhibit a correspondingly high proportion of VCs with PhD partners, suggesting a potential funding gap for research-intensive startups in the region.

These findings highlight the presence of market heterogeneity in the barriers to hiring PhD partners within VC firms, as well as the challenges deep-tech startups face in accessing funding from VCs with strong technical expertise. The geographic imbalance suggests that certain regions may experience greater friction in matching deep-tech firms with suitable VCs, potentially limiting their growth and commercialization prospects.

4.2 Fact 2: Tech-literate VCs are more likely to back deep-tech startups

We next examine whether VCs with higher technology literacy are more likely to invest in deep-tech startups. However, the Pitchbook deal data only captures VC-startup pairs where

VC firms have made actual investments. To test the effect of alumni ties on investment decisions, the sample should include both actual deals and counterfactual pairs—startups that VCs could have considered but chose not to invest in.

Following the methods in Gompers, Mukharlyamov, and Xuan (2016) and Hegde and Tumlinson (2014), we construct plausible counterfactual pairs by identifying, for each year t, a set of VC firms actively making investments and a set of startups actively seeking funding. A VC firm is considered active if it participates in at least one deal in year t. We assume that startups actively seeking funding will either raise funds in a deal or face bankruptcy if they fail to raise capital. Thus, a startup is classified as active if it successfully raises funding or goes bankrupt in year t.

After constructing the active pools, we match VCs with startups based on VCs' investment preferences, considering location (state), industry, and startup development stage (seed rounds, early VC rounds, and late VC rounds). This approach ensures that counterfactual pairs reflect realistic investment opportunities that VCs might have evaluated. Based on this method, 272,323 actual VC-deals generate a total of 13,638,587 VC-startup pairs, including both realized investments and plausible counterfactual opportunities.

The regression specification is

$$\text{Invest}_{ijt} = \beta_1(\text{PhD Ratio}_{jt} \times \text{isDeepTech}_i) + \beta_2\text{PhD Ratio}_{jt} + \eta_i t + \epsilon_{ijt} \tag{1}$$

where the dependent variable Invest_{ijt} represents the investment decision of VC j in startup i in year t. The term PhD Ratio_{jt} denotes the ratio of PhD partners in VC firm j, and isDeepTech_i indicates whether startup i is classified as deep-tech.

The key independent variable of interest, $(\text{PhD Ratio}_{jt} \times \text{isDeepTech}_i)$, captures how a higher ratio of PhD partners in a VC firm influences the likelihood of investing in deep-tech startups relative to non-deep-tech startups. The specification also includes fixed effects, and we test various combinations of fixed effects in Table 3. The standard errors are clustered at VC level.

Table 3 presents the regression results, providing evidence of a positive relationship between the ratio of PhD-holding partners within a VC firm and the likelihood of investing in deep-tech startups. Column (1) includes company-year fixed effects, which absorb all startup-specific characteristics in a given year. The coefficient on the interaction term between the PhD partner ratio and the deep-tech indicator is 0.669, indicating that a 10-percentage-point increase in a VC firm's PhD partner ratio raises the probability of investing in a deep-tech startup by 0.067 percentage points. Relative to the average investment probability of 2.0% in the total matching sample, this represents a 3.3% increase. Besides, the coefficient of the PhD Ratio variable captures the effect on non-deep-tech startups, suggesting that VCs with a higher ratio of PhD partners tend to invest slightly less in non-deep-tech startups, though the effect is not statistically significant.

Recognizing the possibility that time-varying shocks on VCs could simultaneously influence both the hiring of PhD partners and investment strategies, Column 2 introduces VC-Year fixed effects to account for these confounding factors. The coefficient in Column (2) remains similar in magnitude to that in Column (1), indicating that the relationship between technology literacy and deep-tech investment persists even after controlling for within-VC variation over time. Column 3 further controls for time-varying variations in investment patterns by adding VC-Year-State fixed effects. The results across all specifications remain consistent, reinforcing the finding that VCs with higher technology literacy allocate more of their capital toward deep-tech ventures.

Instrumental Variable. As a robustness check, we re-estimate the investment probability using an instrumental variable approach, where the VC firm's PhD partner ratio is instrumented by the average PhD partner ratio of other VCs that invest in the same industry but are located in different states, lagged by one year. The instrument satisfies the relevance condition because PhD hiring practices are correlated across VCs operating in the same industry due to shared technological demands or PhD labor supply, so a higher PhD ratio among out-of-state peers predicts a higher (or lower) PhD ratio for the focal VC. The exclusion restriction is that the PhD composition of out-of-state peers affects the focal VC's investment decisions only through its influence on the VC's own hiring of PhD-trained partners, rather than directly impacting the set of startups it can invest in. To address the possibility that common industry-wide shocks could jointly influence both PhD hiring and deep-tech investment decisions, we include company-year fixed effects, which absorb all startup-specific and industry-year shocks that might otherwise confound the estimates. Meanwhile, using the lagged value of the peer PhD ratio further strengthens identification by mitigating simultaneity concerns: while current peer hiring decisions might be correlated with contemporaneous investment opportunities, their lagged values are predetermined with respect to the focal VC's current investment choices.

Table 4 presents the second-stage results of the instrumental variable estimation. The first-stage F-statistic exceeds 24 in all columns, indicating that the instrument is sufficiently strong. The estimated coefficients are larger in magnitude than those obtained from the OLS specification, suggesting that OLS may underestimate the causal effect of VC technology literacy on deep-tech investment. In Column (1), a 10–percentage-point increase in a VC firm's PhD partner ratio raises the probability of investing in a deep-tech startup by 0.318 percentage points. The coefficient on the *PhD Ratio* variable captures the investment probability for non–deep-tech startups, and its negative sign implies that VCs with more PhD-trained partners are less likely to invest in non–deep-tech ventures. Columns (2) and (3) incorporate VC-year and VC-state-year fixed effects, respectively. While the coefficients become slightly smaller, the estimates remain positive and statistically significant, confirming that VCs with a higher share of PhD-trained partners are more likely to invest in deep-tech ventures.

4.3 Fact 3: Deep-tech startups backed by tech-literate VCs perform better

The previous findings suggest that VCs with a higher ratio of PhD partners are more likely to invest in deep-tech startups. In this section, we examine whether these tech-literate VCs make more successful investments in deep-tech startups. Specifically, we analyze whether a higher proportion of PhD partners within a VC firm leads to better performance outcomes for deep-tech startups. To assess this relationship, we restrict our sample to actual investment deals and estimate the following regression:

$$\text{Performance}_{ijt} = \beta_1 \text{isDeepTech}_i + \beta_2(\text{PhD Ratio}_{jt} \times \text{isDeepTech}_i) + \gamma X_{it} + \eta_{j,t} + \epsilon_{ijt} \quad (2)$$

where Performance_{ijt} represents the exit outcome of startup i that received investment from VC j in year t. The set of performance outcomes includes whether the startup ultimately fails, gets acquired, or goes IPO. The control variables in X_{it} include a dummy variable for whether the startup founder has a PhD, the type of investment deal, the startup's founding year, the state of incorporation, and industry-year fixed effects.. The specification also incorporates VC-year fixed effects to control for unobserved time-varying VC characteristics. Similar to the investment decision analysis, the key coefficient of interest, β_2, evaluates whether VCs with a higher ratio of PhD partners generate better investment outcomes for deep-tech startups compared to non-deep-tech startups.

Table 5 presents the results on startup performance. Column (1) examines the effect of VC technology literacy on the probability of startup failure. The coefficient on the interaction term suggests that a VC firm with a 10-percentage-point higher PhD partner ratio reduces the failure rate of deep-tech startups by 0.363 percentage points compared to non-deep-tech startups. Given the average failure rate of 5.7% in the sample, this represents a relative reduction of 6.4%, indicating that deep-tech startups backed by more technologically proficient VCs are more likely to survive.

Column (2) tests the effects on mergers and acquisitions (M&A). The coefficient on the interaction term is slightly positive but not statistically significant. This may be due to the fact that mergers and acquisitions (M&A) do not always constitute a successful exit, as acquiring firms may purchase shares at a discounted valuation relative to prior funding rounds.

IPOs are generally considered a more favorable exit for VC firms, as the share price at IPO is typically higher than in previous funding rounds. Column (3) examines the effect on the probability of an IPO. The results suggest that a VC firm with a 10-percentage-point higher PhD partner ratio increases the likelihood of a deep-tech startup going public by 0.912 percentage points relative to non-deep-tech startups. Given the average IPO rate of 4.8% in the sample, this represents a relative increase of 19.0%, reinforcing the idea that VCs with greater technology expertise may enhance the growth trajectory of deep-tech startups and facilitate their access to public markets. Column (4) combines the outcomes from Columns (2) and (3), using a dependent variable that indicates whether the startup exits through either an M&A or an IPO. The coefficient on the interaction term remains significantly positive, further supporting the conclusion that technologically proficient VCs enhance exit prospects, particularly through IPOs.

Additionally, the coefficient on the variable isDeepTech captures the performance difference between deep-tech and non-deep-tech firms when invested in by VCs without PhD partners. The results indicate that deep-tech startups exhibit lower failure rates, lower M&A rates, and higher IPO rates, suggesting that they generally perform better than their non-deep-tech counterparts. Overall, these findings suggest that deep-tech startups backed by VCs with greater technology literacy are more likely to achieve successful exits through IPOs and less likely to fail. This can be explained by the hypothesis that VCs with higher technology literacy are better at identifying promising deep-tech startups, and also provide more effective guidance, ultimately adding value to their portfolio companies.

Instrument Variable Similar to the analysis of investment probability, we also estimate the effect of VC technology literacy on investment performance using the same instrumental variable approach. Table 6 reports the second-stage results. Column (1) examines the effect on startup failure. The coefficient on the interaction term $PhDRatio \times DeepTech$ is negative and statistically significant, indicating that deep-tech startups backed by VCs with a higher share of PhD-trained partners are less likely to fail. The magnitude of the IV coefficient is larger than in the OLS estimates: a 10–percentage-point increase in a VC firm's PhD partner ratio reduces the failure rate of deep-tech startups by 1.22 percentage points relative to non–deep-tech startups. Column (2) shows a significant decline in merger activity; however, as discussed earlier, M&A exits can represent both successful and distress-driven outcomes. Column (3) focuses on IPOs and shows that a 10–percentage-point increase in the PhD partner ratio raises the probability of a deep-tech startup going public by 6.15 percentage points relative to non–deep-tech startups. Column (4), which combines IPO and M&A exits, yields a similarly positive and significant effect, suggesting that VCs with greater technological expertise enhance the commercialization potential and exit prospects of their portfolio firms. Overall, the IV results are consistent with the OLS estimates, reinforcing the conclusion that technology-literate VCs play a pivotal role in improving the performance and exit outcomes of deep-tech startups.

5 Model

Section 4 shows that tech-literate VCs are more likely to invest in deep-tech startups, improve their success rates, yet remain scarce, with a geographic variation in market tightness in deep-tech funding. Based on these findings, we develop a dynamic general equilibrium model to explain how constraints in VC firms' technology literacy shape investment patterns and deep-tech financing.

In this model, VC firms and startups meet in a market with search and matching frictions.

The friction generates long-term relationships between VC firms and startups. Time is discrete and infinite.

5.1 VC firms

5.1.1 Productivity and Revenue

VC firms need to hire regular workers $l_{p,j,t}$ to process deals with startups in which they invest, and $z_{j,t}$ is an idiosyncratic productivity shock that follows a log-AR(1) process,

$$logz_{j,t+1} = \rho_z logz_{j,t} + \epsilon_{j,t+1} \tag{3}$$

where $\epsilon_{j,t+1} \sim N(0,\sigma_z^2)$.

The gross revenue of VC firms depends not only on the total size of deals they can handle, but also on the number of startups they match. Therefore, VC firms' revenue $y_{j,t}$ is jointly determined by the demand and supply of capital through a CES aggregator:[4]

$$y_{j,t} = z_{j,t} \left(l_{p,j,t}^{\frac{\sigma-1}{\sigma}} + m_{j,t+1}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where $m_{j,t}$ are the existing deep-tech startups invested by the VC j at the beginning of the period t, and $m_{j,t+1}$ is the total investment of the VC j in deep-tech startups at the end of the period t. We show empirically that deep-tech investments outperform non–deep-tech ones, so VCs' output increases with the share of deep-tech startups invested.

5.1.2 Frictional VC-Startups Investment Market

Investments in deep-tech startups generate better performance (or higher return), but VC firms need to hire specialists (i.e., partners with PhD degrees) to identify new deep-tech startups. Specialists are placed in separate local VC-startup markets and generate s efficiency

[4] $\sigma = 1$ for Cobb–Douglas production function, $\sigma \in (1, \infty)$ is the case of substitution; and $\sigma \in (0,1)$ is the case of complementarity.

units of specialists. Hiring specialists is costly, which is captured by an increasing and convex cost function $\kappa(s)$.

The measure L^b household members serve as startup CEOs, and market frictions imply that they must meet with specialists to obtain VC deals. Here, we assume that the startup CEOs decide independently which local VC-startup markets to visit, and that specialists have finite capacity to screen startups.

Meetings between specialists and potential startup CEOs are thus subject to coordination frictions in the search market: in each period, some local markets have no startup CEOs arriving, while others receive more than the specialists can handle. This friction is captured by a VC-level direct search matching function. When s efficiency units of specialists meet with b units of startup CEOs, they create VC's new startups investment (a measure of new investment relationships):

$$\mathbb{M}(b_{j,t}, s_{j,t}) = \xi \left(b_{j,t}^{\gamma_m} s_{j,t}^{1-\gamma_m} \right)^{\nu} \tag{5}$$

where $\xi > 0$ measures the average matching efficiency, $\gamma_m \in (0,1)$ measures the matching function elasticity and $\nu > 0$ governs the return to scale of this matching technology.[5]

We use $\theta = b/s$ to denote the VC-specific average queue length of potential startups' CEO across a VC's specialists. The probability of matching per specialist, $\frac{\mathbb{M}(b,s)}{s} = \eta(\theta,s) = \xi\theta^{\gamma_m\nu}s^{\nu-1}$, is an increasing function of the queue length. Similarly, the probability of matching per startup, $\frac{\mathbb{M}(b,s)}{b} = \mu(\theta,s) = \xi\theta^{\gamma_m\nu-1}s^{\nu-1}$, is a decreasing function of the queue length.[6]

To capture the fact that startups may exit from the VC's portfolio, we assume that the existing relationships end with probability δ_n each period. Therefore, the size of startups each VC invests, which is a type of customer capital, follows:

$$m_{j,t+1} = (1-\delta_n)(m_{j,t} + \mathbb{M}(b_{j,t}, s_{j,t})) \tag{6}$$

[5]This measure is a product of the exogenous probability of a meeting leading to a new investment relationship, and the measure of meetings taking place.

[6]$\eta(\theta,s) = \mu(\theta,s)\theta$. These expressions capture the idea that an increase in potential startups per specialist increases matches per specialist but at a diminishing rate, because these startup CEOs are more likely to arrive in local markets with specialists occupied.

We assume that VC firms can commit to an upfront cost $\varsigma_{j,t}$ which they use to screen for new deep-tech startups. In equilibrium, different firms incur different upfront costs depending on their desired level of startup investment.[7]

5.2 VC's Recursive Optimization Problem

It follows that the VC's net profit can be written as

$$e_{j,t} = y_{j,t} - s_{j,t}\eta(\theta,s)\varsigma_{j,t} - w_t l_{p,j,t} - w_t \frac{\kappa}{2} s_{j,t}^2 \geq 0 \tag{7}$$

where $\frac{\kappa}{2}s_{j,t}^2$ functions as the adjustment cost of recruiting specialists. The original value of the VC's equity, $v(z,m)$, depends on two state variables $S = (z,m)$, which are productivity and the size of startups.

Every period, a VC firm chooses the number of specialists $s_{j,t}$ to recruit, the amount of upfront costs $\varsigma_{j,t}$ it sacrifices to identify new profitable startups, and output $y_{j,t}$ it produces to maximize its recursive value function:

$$\begin{aligned} v_t(z,m) =& max_{y,s,\varsigma} \;\; e + \beta \mathbb{E}^{\nu}{}_t v_{t+1}(z', m') \\ e =& y - s\eta(\theta, s)\varsigma - w_t l_p - w_t \frac{\kappa}{2} s^2 \\ y =& z \left(l_p^{\frac{\sigma-1}{\sigma}} + m'^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\ m' =& (1-\delta_n)(m + s\eta(\theta,s)) \\ log(z') =& \rho_z log(z) + \epsilon_z \end{aligned} \tag{8}$$

with $\mu(\theta, s)\varsigma = w_t + \Delta$, where Δ represents the premium (or cost) of being a startup owner to households (VC firms), relative to engaging in market work for VCs (e.g., production or sales) when households make their decisions. Startup owners can be indifferent between low–upfront-cost and high–upfront-cost VCs if queues at high–upfront-cost VCs are suffi-

[7] In practice, we assume that the startup depreciation rate is large enough to ensure that the VC continues hiring some specialists each period, even when a low productivity realization causes overall contraction.

ciently shorter than those at low–upfront-cost VCs. All choice variables are nonnegative.

Proposition 2: The optimal conditions of VC imply

1. $\frac{w+\Delta}{w}\theta = \frac{\gamma_m}{1-\gamma_m}\kappa s$
2. $\varsigma = \frac{w+\Delta}{\xi}\theta^{1-\gamma_m}$

5.3 Household Sector

There is a unit measure continuum of identical households with preferences over consumption C_t and total labor supply—comprising market work L_t^m for VC firms and funding search as startup owners L_t^b in the VC-startup market—whose expected utility is given by

$$\sum_{t=0}^{\infty} \beta^t u(C_t, L_t^b + L_t^m),$$

subject to the budget constraint

$$C_t + \frac{B_{t+1}^{rf}}{1+r_t} \leq w_t(L_t^b + L_t^m) + B_t^{rf} + T_t, \tag{9}$$

where β is the discount factor for households, r_t is the risk-free rate, w_t is the wage rate, B_t^{rf} is risk-free debt for a period and T_t are transfers from all firms, including nominal profits.

In each period, households allocate one unit of time between market work and funding search activities. This allocation determines the real wage via the following optimality condition:

$$w_t = -\frac{U_l(C_t, L_t^b + L_t^m)}{U_c(C_t, L_t^b + L_t^m)}. \tag{10}$$

Households' decisions over consumption and risk-free bond holdings determine the risk-free rate.

5.4 Model Equilibrium

Given equilibrium prices w and r, a stationary competitive search equilibrium specifies VC decision rules $y(S;w,r), s(S;w,r), l_p(S;w,r)$, $\varsigma(S;w,r), e(S;w,r)$ and their value function $v(S;w,r)$ such that (1) VCs' decision rules and their value function solve their problems; (2) regular worker satisfies $\mu(\theta,s)\varsigma = w+\Delta$ and $\theta > 0$; (3) all markets clear:

Consumption goods market clears. The total of consumption and the job premium should equal the total revenue in the economy.

$$C_t + \int \Delta d\phi(S) = Y_t = \int y_t d\phi(S). \tag{11}$$

Matching consistency. In the competitive search market, the total number of startup owners should be equal to the total number of Ph.D. partners matched.

$$L^b = \int s\theta d\phi(S). \tag{12}$$

Labor market clears. The aggregate demand of labor that includes regular worker and Ph.D. partners should equal the total supply of labor doing market work L^m, and we exogenously set the total labor supply $L^m + L^b$ in this economy to 0.6:[8]

$$L^d = \int \left(\frac{\kappa}{2}s^2 + l_p\right) d\phi(S) = L^m. \tag{13}$$

6 Quantitative Analysis

We study the model solution and perform quantitative analysis by means of calibration and simulation. We start with an explanation of annual calibration and simulation, followed by a discussion on the model mechanisms and policy function. We solve for steady-state equilibrium via value function iteration. To compare our model with the data, we simulate

[8] $L^m + L^b = \int \left(\frac{\kappa}{2}s^2 + l_p + s\theta\right) d\phi(S) = 0.6.$

a panel of 5,000 firms and 50 years for 10 times, and compute the cross-sample average of the target moments.

6.1 Model Calibration

The calibration is summarized in Table 7. We take parameter values reported in the literature whenever possible and choose the rest of them to match the data moments from the empirical sample. The parameters can be divided into three groups that affect the supply of Ph.D. partners, demand, and supply of capital.

The supply of capital from VC depends on an exogenous productivity process that affects VC's valuation and earnings. We calibrate the parameters that govern capital supply: $\rho_z = 0.75, \sigma_z = 0.1$ to match the average ratio of earnings per capital and the correlation of VC earnings. We calibrate the degree of complementarity: σ between the supply and demand of capital to match the labor ratio of startup owners to the total number of regular workers and Ph.D. partners.

The demand for capital from deep-tech startups is sticky and requires effort from Ph.D. partners to accurately identify high-potential deep-tech startups for investment. This process entails substantial search costs, such as the regular wages paid to Ph.D. partners, as well as upfront costs associated with screening deep-tech from non–deep-tech startups. Each year, some existing deals expire while new ones are initiated. Consequently, the stock of invested deep-tech capital is a state variable that follows a law of motion. We back out the depreciation rate of invested deep-tech capital $\delta = 0.25$ from the average growth rate of total invested deep-tech capital and the average ratio of the new investment to total invested deep-tech capital. We calibrate the matching efficiency ξ to be 0.25 to match the observed average ratio of new investment to total invested deep-tech capital. Finally, γ_m is set to 0.6 to match the average ratio of the number of Ph.D. partners to the number of deep-tech startups invested in.

Search frictions limit the hiring of Ph.D. partners by increasing hiring costs, measured by the total wage expense on Ph.D. partners. We calibrate κ to 4 to match the average ratio of total wage expenses for other employees to those for Ph.D. partners. Households face a wage premium Δ from being startup owners relative to working for VC firms when making occupational choices each period. By default, we set this wage premium (or the relative cost of screening startups for VC firms) to zero.

6.2 Model Implication

In this section, we test two model implications. The first one is about the predictability of labor share of Ph.D. partners to other employees about the VC investment rate, valuation, and returns. Second, we examine the predictability of market tightness.

6.2.1 Labor Share, Investment, and Valuation

The model mechanism suggests that VC with a higher labor share of Ph.D. partners to other employees: $s/(l_p + s)$, predicts a higher investment rate and a higher VC value. We use the simulation data to estimate the following regression specification:

$$y_{i,t+1} = \alpha_i + \frac{s_{i,t}}{s_{i,t} + l_{p,i,t}} + \epsilon_{i,t+1} \tag{14}$$

where $y_{i,t+1}$ is the VC investment rate defined as the cost of hiring Ph.D. partners (wage expense) per capital: $\frac{w\kappa s^2}{2m}$, or the ratio of new investment to total capital invested $\frac{\mathbb{M}}{m}$, or IRR in percentage. Panel A of Table 8 shows that the coefficient estimates of the labor share are all positive: more Ph.D. partners lead to more investment in deep-tech startups relative to non-deep-tech startups and therefore earn a higher return.

6.2.2 Heterogeneous Market Tightness

In the model, the tightness of the market is represented by $\theta = b/s$. A higher value of θ indicates that there is relatively more funding needed from deep-tech startups than funding supply from VCs. In other words, VCs have more bargaining power than start-ups when structuring deals and negotiating the division of earnings. Therefore, a less tight market, indicated by a higher value of θ, predicts more investment and a higher return on VC investment. Panel B of Table 8 shows the coefficient estimates of market tightness θ.

7 Counterfactual Analysis

How does the wage premium (the cost of becoming a partner) Δ in households' occupational choice affect the equilibrium composition of labor and the return on VC deep-tech investment? To address these questions, we use the calibrated model to conduct a counterfactual analysis in this section.

In the baseline model, the aggregate labor supply is set exogenously to 0.6. In the counterfactual analysis, we vary Δ from 0 to 0.3 and solve the equilibrium ratio at the aggregate level.

Figure 3 plots the aggregate values of three types of labor: regular workers l_p, Ph.D. partners s, start-up owners b, and labor share for VC firms $\frac{l_p}{l_p+s}$, as well as wage rate and the IRR of VC. As the marginal cost of screening for profitable deep-tech startups increases, the equilibrium number of startups b decreases, leading to a decline in the total invested deep-tech capital. Due to the complementarity between regular labor and invested deep-tech capital, the total demand for regular labor l_p also decreases.

A more interesting observation is the hump-shaped pattern in the equilibrium number of Ph.D. partners. Reducing the cost of becoming a Ph.D. partner does not necessarily increase the equilibrium share of Ph.D. partners. From Proposition 2, equilibrium hiring of Ph.D. partners is positively related to both the equilibrium number of startup owners and the relative marginal cost $\frac{\Delta}{w}$ of hiring Ph.D. partners. As the number of startup owners decreases, the relative marginal cost also falls ($i.e$, $\frac{\Delta}{w}$ increases), generating a hump-shaped relationship in equilibrium Ph.D. hiring.

As a side note, the joint hump-shaped patterns of Ph.D. partners and wage rates imply a U-shaped relationship in the IRR. This indicates that the relative wage premium (or cost) plays a key role in determining returns as labor supply increases. When the wage premium Δ for becoming a startup owner is high, expanding the equilibrium number of Ph.D. partners can reduce the IRR by up to 4%. This is due to the rising cost of hiring Ph.D. partners outweighs the additional returns generated from their investment in deep-tech startups.

The hump-shaped relationships between the equilibrium share of Ph.D. partners and Δ, and between IRR and Δ, help explain the persistently low and declining presence of Ph.D.-trained partners in VC firms. When the cost of becoming a partner is high, few Ph.D.s enter the industry, while equilibrium returns remain high. Consequently, VC firms face weak incentives to recruit more Ph.D. partners, leading to a market equilibrium characterized by structurally low technology literacy among VCs.

8 Conclusion

This paper investigates the role of technology literacy among VC firms in shaping deep-tech investment decisions and startup outcomes. Our findings reveal that VCs with a higher ratio of PhD partners are significantly more likely to invest in deep-tech startups. Moreover, startups backed by tech-literate VCs exhibit better performance, as measured by lower failure rates and higher IPO probabilities. These results suggest that technology literacy plays a crucial role in both the selection and success of deep-tech startups, reinforcing the idea that domain expertise enhances the ability of VCs to evaluate, support, and guide research-intensive ventures.

Despite the advantages of technologically literate VCs, our analysis reveals a persistent scarcity of Ph.D.-trained partners in the VC industry and significant geographic variation in market tightness for deep-tech funding. While deep-tech startups are heavily concentrated in regions such as California, the supply of VCs with the technical expertise to assess and support them remains disproportionately low. This imbalance implies that deep-tech startups in certain regions face higher funding frictions.

To formalize these insights, we develop a structural model with search and matching frictions that explains why tech-literate VCs remain limited. The model shows that reducing the cost for Ph.D.s to become VC partners does not necessarily increase their equilibrium share, providing an explanation for the persistently low—and recently declining—representation of Ph.D. partners in the industry.

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Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Q25	Median	Q75	Max
PhD Ratio	262,455	0.0781	0.1686	0	0	0	0.0789	1
Deep Tech Indicator	262,455	0.3059	0.4608	0	0	0	1	1
Year Founded	262,455	2015.106	4.8966	2000	2012	2016	2019	2023
Founders with PhD	241,189	0.2004	0.4003	0	0	0	0	1
Closed	262,455	5.7393	23.2592	0	0	0	0	100
Merged	262,455	17.4316	37.9381	0	0	0	0	100
IPO	262,455	4.8107	21.3993	0	0	0	0	100

Notes: This table reports summary statistics for key variables at VC-startup-deal level. isDeepTech is a binary variable indicating whether a firm has posted at least one job listing requiring a PhD. Total Raised represents the cumulative amount of funding secured by a firm before exit or shutdown. Close is a binary variable equal to 100 if the firm is categorized as ”Out of Business,” ”Bankruptcy: Liquidation,” or ”Bankruptcy: Administration/Reorganization,” and 0 otherwise. M&A is a binary variable taking a value of 100 if the firm exits via a merger or acquisition and 0 otherwise. IPO is a binary variable equal to 100 if the firm has undergone an initial public offering and 0 otherwise.

Table 2: Deep-Tech Companies and Tech-Literate VC by State

State	DT Startup Count	Tech-Literate VC Ratio	DT Company Ratio
California	1,057	0.10	0.26
New York	301	0.10	0.17
Massachusetts	297	0.23	0.39
Texas	110	0.14	0.17
Washington	72	0.16	0.19
Colorado	68	0.19	0.23
Pennsylvania	59	0.24	0.23
Illinois	55	0.15	0.17
Florida	48	0.13	0.10
Delaware	46	0.11	0.10

Notes: This table reports the number of deep-tech (DT) startups by state in 2022, along with the tech-literate VC Ratio and DT Company Ratio. The tech-literate VC Ratio represents the proportion of VCs with at least one PhD partner as a share of the total number of VCs who made investments in the state in 2022. The DT Company Ratio reflects the share of Deep-Tech companies relative to all startups that received funding in the state in 2022. The data sample is consistent with our regression analysis dataset, which includes all VC deals on US startups founded between 2000 and 2023.

Table 3: Investment Decision

	Invest		
	(1)	(2)	(3)
PhD Ratio	-0.0748		
	(0.0695)		
PhD Ratio × Deep Tech	0.669***	0.654***	0.619***
	(0.136)	(0.133)	(0.133)
Company × Year FE	Y	Y	Y
VC × Year FE		Y	Y
VC × State × Year FE			Y
Observations	12,942,374	12,938,382	12,921,473
R^2	0.259	0.257	0.224

Notes: This table estimates the effects of the ratio of PhD-holding partners on investment choice. The dependent variable is an indicator that equals 100 if the VC invests in the startup and 0 otherwise. The main variable of interest, *isDeepTech*×*PhDRatio*, is the interaction between *isDeepTech*, an indicator that equals 1 if the startup has job postings requiring a PhD, and *PhDRatio*, the proportion of PhD-holding partners within the VC firm. Column (1) includes company-year fixed effects. Column (2) further adds VC-year fixed effects, while Column (3) includes VC-year-state fixed effects. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 4: Investment Decision - Instrument Variable

	Invest		
	(1)	(2)	(3)
PhD Ratio	-2.410***		
	(0.776)		
PhD Ratio × Deep Tech	3.181***	1.844**	1.847**
	(0.968)	(0.914)	(0.924)
Company × Year FE	Y	Y	Y
VC × Year FE		Y	Y
VC × State × Year FE			Y
Observations	9,385,501	9,383,570	9,369,889
F-statistic	24.64	67.76	66.36
R^2	-0.000	-0.000	-0.000

Notes: This table reports the second-stage results of the instrumental variable estimation examining the effect of VC technology literacy on investment decisions. The dependent variable is an indicator equal to 100 if the VC invests in the startup and 0 otherwise. The endogenous variable *PhDRatio*, defined as the proportion of PhD-holding partners within the VC firm, is instrumented by the peer PhD ratio Z_{t-1}, which is the lagged average PhD ratio of other VCs that invest in the same industry but are located in different states. The interaction term $PhDRatio \times DeepTech$ is instrumented by $Z_{t-1} \times$ DeepTech. The variable *DeepTech* equals 1 if the startup has job postings requiring a PhD. Column (1) includes company-year fixed effects. Column (2) adds VC-year fixed effects, and Column (3) further includes VC-state-year fixed effects. F-statistics are the Kleibergen–Paap rank Lagrange Multiplier statistic from the first-stage regressions. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Investment Performance

	Close (1)	**M&A** (2)	**IPO** (3)	**M&A and IPO** (4)
PhD Ratio × Deep Tech	-3.631***	0.289	9.118***	0.0798***
	(0.961)	(1.597)	(1.774)	(0.0161)
Deep Tech	-1.386***	-5.714***	5.737***	-0.0149***
	(0.137)	(0.318)	(0.333)	(0.00298)
Controls	Y	Y	Y	Y
VC × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
Observations	219,878	219,878	219,878	219,878
R^2	0.263	0.358	0.481	0.410

Notes: This table reports the effects of the ratio of PhD-holding partners on investment performance. VC-year fixed effects and industry-year fixed effects are included. Control variables include the startup's founding year, whether the startup has a PhD founder, deal type, and the headquarter state. The dependent variable in Columns (1), (2), and (3) is a binary indicator equal to 100 if the startup fails, is acquired, or goes public (IPO), respectively. Column (4) uses a dependent variable equal to 100 if the startup exits through either an M&A or an IPO. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 6: Investment Performance - Instrument Variable

	Close (1)	**M&A** (2)	**IPO** (3)	**M&A and IPO** (4)
PhD Ratio × Deep Tech	-12.22***	-19.64***	61.50***	0.331***
	(3.026)	(5.407)	(8.242)	(0.0585)
Deep Tech	-0.750***	-4.333***	1.642**	-0.0365***
	(0.245)	(0.536)	(0.696)	(0.00538)
Controls	Y	Y	Y	Y
VC × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
Observations	184,032	184,032	184,032	184,032
F-statistic	102	102	102	102
R^2	0.001	0.004	-0.017	-0.002

Notes: This table reports the second-stage results of the instrumental variable (IV) estimation examining the effect of VC technology literacy on investment performance. The endogenous variable, *PhDRatio*, defined as the proportion of PhD-holding partners within the VC firm, is instrumented by the lagged average PhD ratio of other VCs that invest in the same industry but are headquartered in different states (Z_{t-1}). The interaction term $PhDRatio \times DeepTech$ is instrumented by Z_{t-1} × DeepTech. All specifications include VC-year and industry-year fixed effects. Control variables include the startup's founding year, whether the startup has a PhD founder, deal type, and the state of incorporation. The dependent variable in Columns (1), (2), and (3) is a binary indicator equal to 100 if the startup fails, is acquired, or goes public (IPO), respectively. Column (4) uses a dependent variable equal to 100 if the startup exits through either an M&A or an IPO. F-statistics are the Kleibergen–Paap rank Lagrange Multiplier statistic from the first-stage regressions. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 7: Model Calibration

Parameter	Value	Moments	Data	Model
ρ_z	0.75	Earnings Correlation	0.82	0.78
σ_z	0.1	Earnings/Capital	0.22	0.20
δ	0.25	Average capital growth	0.25	0.24
γ_m	0.6	# of Ph.D./# of Startups	0.66	0.62
ξ	0.1	Average new investment to existing capital	0.33	0.32
κ	4	$\frac{\text{Wage expense on other labor}}{\text{Wage expense on Ph.D. partners}}$	1.6	1.18
σ	0.15	IRR (%)	3.8%	2.8%
Δ	0	$\frac{\text{Startup Owners}}{\text{Regular Employees + Ph.D. Partners}}$	1	0.92
β	0.97	Annual risk-free rate	3%	3%

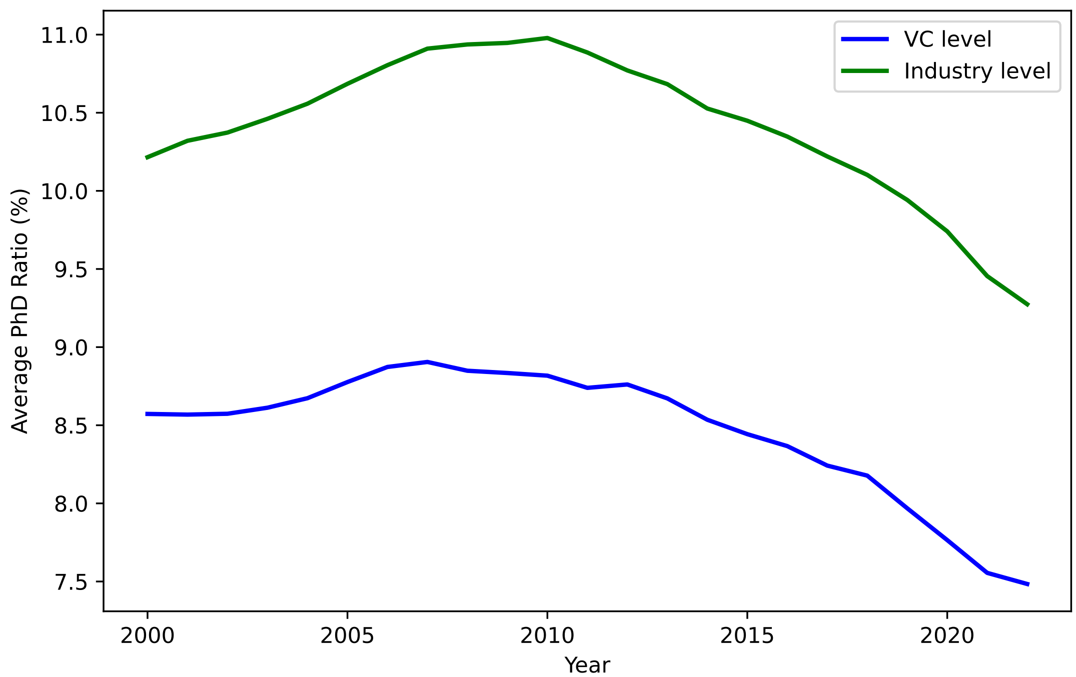
Notes: This table reports the values of calibrated parameters in the model and the matched moments in the data and model.

Table 8: Model Implication

	Investment Rate	Matched Rate	IRR (%)
		Panel A	
Labor Share	0.61	1.37	0.11
		Panel B	
Market Tightness $\frac{b}{s}$	0.14	0.21	8.71

Notes: This table presents model implications using simulated data from the calibrated model. Panel A estimates the predictability of VC labor share, defined as the ratio of Ph.D. partners to the total of employees, on VC's investment rate, new matched investment relationship, and IRR. Panel B estimates the predictability of market tightness θ, defined as the ratio of startups to Ph.D. partners, on VCs' investment and return.

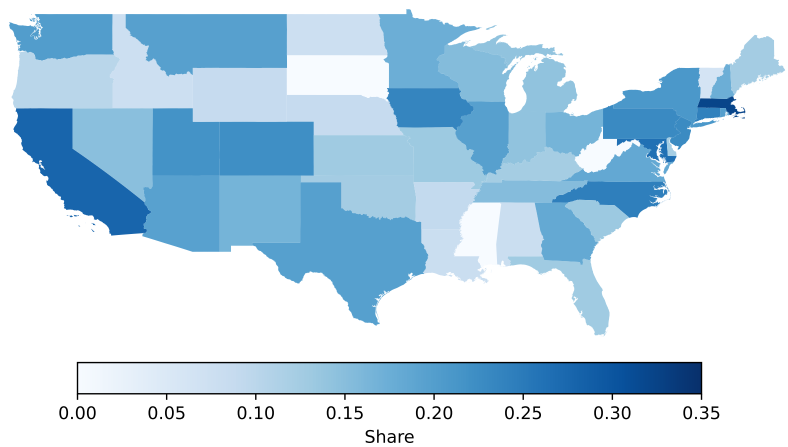
Figure 1: PhD in the VC Industry



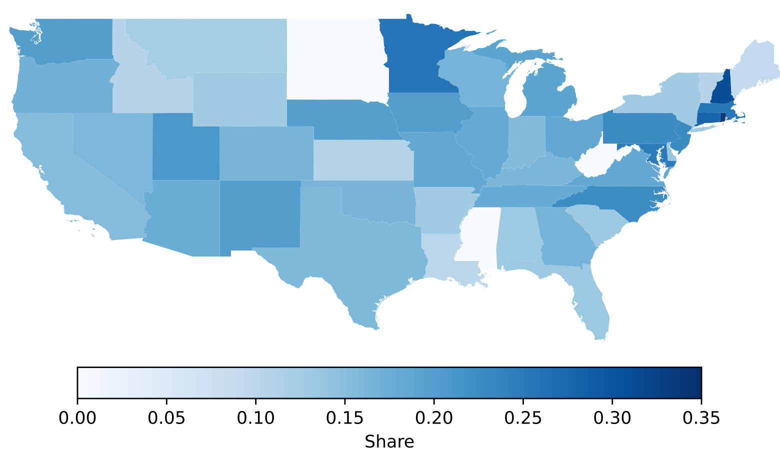
Notes: This figure plots the ratio of PhD partners in the VC industry. The green line represents the overall share of PhD partners among all VC partners in the industry. It is calculated as the total number of PhD partners divided by the total number of partners in the VC industry for each year. The blue line measures the average ratio of PhD partners at the firm level, computed as the mean PhD ratio across VC firms in each year. The data is sourced from PitchBook, and the sample corresponds to the dataset used in our regression analysis, which includes all VC firms that have participated in at least one deal involving U.S. startups founded between 2000 and 2023.

Figure 2: Geographical Distribution of Deep-Tech Startups and VCs

(a) Share of Deep-Tech Startups

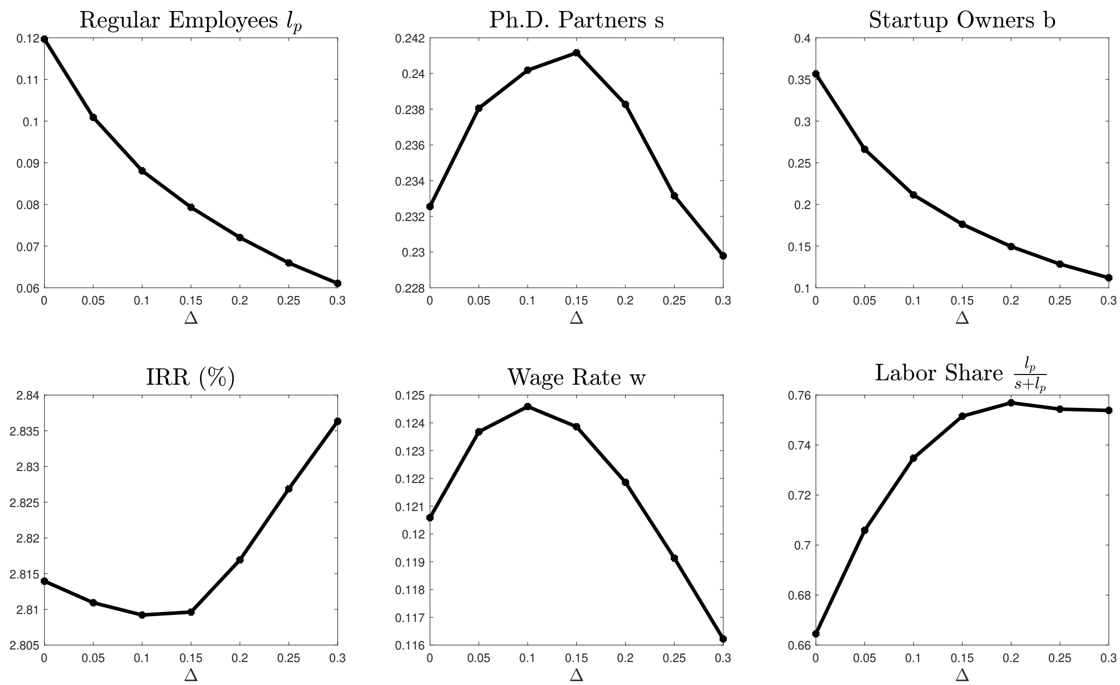


(b) Share of VCs with PhD Partner(s)



Notes: This figure reports the ratio of deep-tech startups along with the tech-literate VC Ratio by state. The median is used when aggregating data from the state-year level to the state level. Figure (a) plots the share of deep-tech startups relative to all startups that received funding in the state during the same period. Figure (b) plots the proportion of VCs with at least one PhD partner as a share of the total number of VCs who made investments in the state that year. The data sample is consistent with our regression analysis dataset, which includes all VC deals involving U.S. startups founded between 2000 and 2023.

Figure 3: Counterfactual Analysis: Aggregate Labor and IRR



Notes: This figure plots the VC aggregate internal rate of return and the aggregate labors from model equilibrium when we exogenously vary wage premium (cost) Δ from 0 to 0.3.

A Appendix

The following tables examine the empirical results using an industry-level deep-tech definition instead of a startup-level classification. To benchmark industries, we calculate the proportion of firms advertising PhD- or MD-related positions within each of the 41 PitchBook industries. Three industries—Other Information Technology, Other Consumer Products and Services, and Other Healthcare—are excluded due to their limited use as primary industry classifications. All other industries are ranked based on the fraction of deep-tech firms, with startups operating in industries below the median ratio categorized as "low tech."

Table A.4 replicates the regressions in Table 3, replacing the variable isDeepTech with isLowTech. Similarly, Table A.5 follows the regressions in Table 5. The results reinforce the same conclusion: VCs with a higher proportion of PhD-holding partners invest less in low-tech industries, and investments in these industries tend to exhibit weaker performance.

A.1 Algorithm

Guess the wage rate w,

1. Given the state variables (z,m), have an initial guess of the expected value $E_z V^0_{t+1}(z, m')$
2. Solve the maximization problem for optimal investment (hiring) s and value function $V_t(z,m)$.
3. Compute the expected value at time t: $E_z V^0_t(z_{-1}, m)$
4. Compute the error of the expected value function:

$$\epsilon = \max |E_z V_{t+1}(z, m') - E_z V_t(z_{-1}, m)|$$

   and update the expected value function: $E_z V^{new}_{t+1}(z, m') = E_z V^0_t(z_{-1}, m)$.
5. Iterate the above procedure until the error of the expected value function is small enough.

Compute the ergodic distribution $\phi(z,m)$ implied by policies, perform aggregation of labor, and use the labor market clearing condition to update the wage rate.

A.2 Optimal Conditions

This section derives the optimal conditions:

$$\begin{aligned}
v_t(z,m) =& max_{l,s,\varsigma,\theta} \;\; e + \beta \mathbb{E}^{\nu}{}_t v_{t+1}(z', m') \\
e =& y - w_t l_p - s\eta(\theta, s)\varsigma - w_t \frac{\kappa}{2} s^2 \\
y =& z \left(l_p^{\frac{\sigma-1}{\sigma}} + m'^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\
m' =& (1-\delta_n)(m + s\eta(\theta,s)) \\
log(z') =& \rho_z log(z) + \epsilon_z \\
\mu(\theta,s)\varsigma =& w_t + \Delta
\end{aligned}$$

Choice variables (l_p,s,ς,θ), optimal condition:

[l_p]

$$l_p = m' \left[(w/z)^{\sigma-1} - 1 \right]^{\frac{\sigma}{1-\sigma}} \tag{15}$$

[s]

$$w \frac{\kappa'(s)}{\eta(\theta)} + \varsigma = V_m \tag{16}$$

[ς]

$$\varsigma = \gamma_m V_m \tag{17}$$

The above two equations together give the following:

$$w \frac{\kappa'(s)}{\eta(\theta)} = \left(\frac{1}{\gamma_m} - 1 \right) \varsigma \tag{18}$$

Household's indifference condition for occupational choices is

$$\mu(\theta)\varsigma = w + \Delta \tag{19}$$

which is

$$\varsigma = (w + \Delta)/(\xi \theta^{\gamma-1})$$

The above two equations (18) and (19) give

$$\kappa'(s) \frac{\gamma_m}{1 - \gamma_m} = \frac{w + \Delta}{w} \theta$$

Table A.1: Samples of Firms with and without Job Posting

Variable	Mean (without)	SD (without)	Mean (with)	SD (with)	Diff
Year Founded	2013.026	6.218	2013.519	6.150	0.493
Close	0.316	0.468	0.077	0.267	-0.239
M&A	0.151	0.358	0.142	0.348	-0.009
IPO	0.011	0.147	0.022	0.146	0.011
Total Raised	15.899	159.327	74.528	542.128	58.629
Founder Count	1.532	0.787	1.701	0.932	0.169
Founder PhD Count	0.228	0.550	0.239	0.609	0.011
Founder PhD Ratio	0.145	0.331	0.136	0.316	-0.009

Notes: This table reports summary statistics for firms without job postings and firms with job postings. Close is a binary variable equal to 1 if the firm is categorized as "Out of Business," "Bankruptcy: Liquidation," or "Bankruptcy: Administration/Reorganization," and 0 otherwise. M&A is a binary variable equal to 1 if the firm exits via a merger or acquisition and 0 otherwise. IPO is a binary variable equal to 1 if the firm has undergone an initial public offering and 0 otherwise.

Table A.2: Distribution of Major Fields and PhD Ratios

Major Field	Count	PhD Ratio
Business	64,412	0.0078
Other	46,846	0.1681
Media/Art/Design	16,702	0.0096
Finance/Accounting	10,374	0.0139
Other Engineering	9,878	0.1187
Computer Science	9,250	0.0692
Economics	7,851	0.0218
Psychology	4,322	0.0539
Politics	3,759	0.0245
Education	3,331	0.1225
Biology	2,805	0.2510

Notes: This table presents the distribution of individuals working in the VC industry by the major field of their highest degree and the corresponding PhD ratios. The data is sourced from Revelio Labs rather than PitchBook, as Revelio Labs provides better coverage of non-partner roles in the VC industry, including analysts and associates. The sample of VC firms and partners is consistent with our regression analysis dataset, which includes all VC firms who participated in at least one VC funding round for a US startup founded between 2000 and 2023.

Table A.3: Major Concentrations of Partners' Highest Degree

Panel A: Bachelor	
Major Concentration	Count
Economics	814
Computer Science	399
Business Administration	360
Finance	352
Political Science	168
Panel B: Master's	
Major Concentration	Count
Finance	945
Computer Science	354
Business	310
Management	276
Business Administration	263
Panel C: Ph.D.	
Major Concentration	Count
Computer Science	166
Medicine	160
Electrical Engineering	134
Physics	104
Biochemistry	103

Notes: This table presents the distribution of major fields for VC partners' highest academic degrees, categorized by Bachelor's, Master's, and PhD levels. The data reflects the educational backgrounds of VC partners, highlighting the prevalence of degrees in economics, finance, and business. The data is from PitchBook. The sample of VC firms is consistent with our regression analysis dataset, which includes all VC firms who participated in at least one VC funding round for a US startup founded between 2000 and 2023.

Table A.4: Investment Decision

	Invest		
	(1)	(2)	(3)
PhD.Ratio	0.3493**		
	(0.1707)		
PhD.Ratio × isLowTech	-0.4579***	-0.4801***	-0.4801***
	(0.1035)	(0.1101)	(0.1101)
VC FE	Y	Y	Y
Year FE	Y	Y	Y
Company FE	Y	Y	Y
VC×Year FE		Y	
State FE			Y
Observations	10,427,762	10,427,762	10,427,762
R^2	0.23503	0.24444	0.24444

Notes: This table estimates the effects of the ratio of PhD-holding partners on investment choice. The dependent variable is an indicator that equals 1 if the VC invests in the startup and 0 otherwise. The main variable of interest, *isDeepTech×PhDRatio*, is the interaction between *isDeepTech*, an indicator that equals 1 if the startup has job postings requiring a PhD, and *PhDRatio*, the proportion of PhD-holding partners within the VC firm. Column (1) includes VC fixed effects, year fixed effects, and company fixed effects. Column (2) further adds VC-year fixed effects, while Column (3) includes VC-year and state fixed effects. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.5: Investment Performance

	Close (1)	**M&A** (2)	**IPO** (3)	**M&A and IPO** (4)
isLowTech	1.471***	5.755***	-6.000***	1.674***
	(0.1735)	(0.3892)	(0.3727)	(0.3736)
isLowTech × PhD.Ratio	0.1762	2.303	-5.175***	-0.8234
	(1.184)	(2.125)	(1.710)	(2.086)
VC×Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	182,405	182,405	182,405	182,405
R^2	0.31831	0.41627	0.48798	0.45308

Notes: This table reports the effects of the ratio of PhD-holding partners on investment performance. VC-year fixed effects and industry fixed effects are included. Control variables include the startup's founding year, whether the startup has a PhD founder, and deal type. The dependent variable in columns (1), (2), and (3) is a dummy variable indicating startup failure, merger and acquisition (M&A), and IPO, respectively. The dependent variable in column (4) is an indicator variable for either M&A or IPO. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.