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

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Abstract

This paper examines how technology literacy within venture capital (VC) firms affects investment in deep-tech startups. Using novel data linking PitchBook and Revelio Labs, we show that tech-literate VCs (proxied by share of PhD-trained partners) are scarce, geographically concentrated, and more likely to fund deep-tech ventures. Startups backed by such VCs exhibit lower failure rates and higher IPO probabilities. We develop and calibrate a dynamic matching model with hiring frictions of PhD-trained partners to explain these patterns. Our findings highlight how limited investor expertise contributes to market tightness in deep-tech funding and shapes both the allocation and performance of capital to innovation.

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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 commercialize effectively.

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 novel empirical 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 investors 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.

We next 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 3.2%, 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.

The final empirical finding tests 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 10.6% and increases the IPO probability by 16.7%. 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.

Each period, VC firms compete to match with startups and generate revenue from successful investments. Their operations are constrained along 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. 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 and standard deviation of VC profitability, 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, VCs with higher productivity levels find it optimal to invest more heavily in hiring PhD partners and screening 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 high (i.e., when the number of deep-tech startups relative to VC Ph.D. partners is larger), investors obtain higher returns due to improved bargaining power.

This research contributes to three key 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 investors 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.

Our findings have important implications for policymakers, investors, and startup founders. For policymakers, policies that incentivize PhD holders to transition into VC careers or promote industry-academic partnerships could help bridge the funding gap for deep-tech startups. For VC firms, hiring more partners with technical backgrounds could improve investment decisions and increase returns in deep-tech sectors. For deep-tech startups, our findings highlight the importance of securing investors who not only provide capital but also possess the technical expertise necessary for navigating the challenges of commercializing breakthrough innovations.

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 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 investors 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

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

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 venture capital, 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, investors 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 deep 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 investors 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 venture capital investors 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).

Revelio Labs Data We obtain employer-employee matched data from Revelio Labs, which is underlied by LinkedIn data. Revelio Labs is a workforce intelligence platform that tracks over 1.1 billion of 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

[2]PitchBook data as of February 2025.

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 27,917 startups, 12,261 investors, and 67,065 deals. The regression is at the investor-startup-deal level with sample size of 182,405. Table 1 presents the summary statistics for key variables used in the analysis, with the observation level at the investor-startup-deal level. The majority of VC firms in the deals do not have any PhD partners, with an average PhD partner ratio of 7.8%, indicating that high technology literacy is relatively uncommon among VC firms. In the sample, 28.1% of VC deals involve deep-tech startups are classified as Deep-Tech. [3] Regarding exit performance, 6.15% of startups in the deal fail or go bankrupt. Meanwhile, 17.17% of startups in the deal exit through mergers or acquisitions (M&A), and 4.08% 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 investors 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 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

[3] At the startup level, 16% of firms are classified as deep-tech, whereas at the VC-deal level, 28.1% of deals involve deep-tech startups.

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 investors, the geographic distribution of deep-tech startups and PhD-backed investors 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 investors 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 investors 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 investors with strong technical expertise. The geographic imbalance suggests that certain regions may experience greater friction in matching deep-tech firms with suitable investors, 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 investor-deals generate a total of 13,638,587 VC-startup pairs, including both realized investments and plausible counterfactual opportunities.

The regression specification is

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

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 includes investor fixed effects (η_j), startup fixed effects (η_i), and year fixed effects (η_t), controlling for time-invariant differences across investors and startups, as well as broader market trends. 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. In Column 1, the coefficient of the interaction term is 0.64, 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 0.064 percentage points. Relative to the average investment probability of 2.0% in the total matching sample, this represents a 3.2% 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 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. Column 3 further controls for time-varying variations in investment patterns by adding VC-Year-State-Industry 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.

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. isDeepTech_i is an indicator for whether the startup has any job posting to recruit PhDs, and an interaction term $(\text{isDeepTech}_i \times \text{PhD Ratio}_{jt})$.

The control variables in X_{it} include a dummy variable for whether the startup founder has a PhD, the type of deals, the startup's founding year, and its primary industry classification. The specification also incorporates investor-year fixed effects, $\eta_{j,t}$, to control for unobserved time-varying investor 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 4 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 0.34 percentage points compared to non-deep-tech startups. Given the average failure rate of 3.2% in the sample, this represents a relative reduction of 10.6%, 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 negative 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 0.73 percentage points relative to non-deep-tech startups. Given the average IPO rate of 4.37% in the sample, this represents a relative increase of 16.7%, 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 results align closely with those in Column (3), further supporting the notion that technologically proficient VCs improve 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.

5 Model

Section 4 shows that tech-literate VCs are more likely to invest in deep-tech startups, improve their success rates, and 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 routine workers $l_{j,t}$ 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,

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

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

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:

$$\begin{aligned} y_{j,t} &\leq z_{j,t} l_{j,t} \\ y_{j,t} &\leq m_{j,t} + \mathbb{M}_{j,t} \end{aligned} \tag{4}$$

where $m_{j,t}$ are the existing deep tech startups invested by the VC j' and $\mathbb{M}_{j,t}$ is the new deep tech startups matched in a frictional search and matching market in year t.[4]

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 (proxy by partners with PhD degree) to identify new deep-tech startups. Specialists are placed in separate local VC-startup markets and generate s efficiency 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 startups CEO and the market frictions imply that they must meet with the specialists to get the VC deals. Here we assume that

[4] Or equivalently, the ratio of deep-tech startups to all non-deep-tech startups. Here we normalize the total number of non-deep-tech startups to 1.

the startups CEO decide on the local VC-startup markets to visit independently and that specialists have finite capacity to screen the startups.

Meetings between specialists and potential startups CEO are thus subject to coordination frictions in the search market; each period some local markets go without any startups CEO arriving, while others get 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 startups CEO, 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:

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

We assume that VC firms can commit to an upfront cost $\varsigma_{j,t}$, which they use to screen for new profitable startups. In equilibrium, different firms have different upfront costs, depending on their desire to expand startups investment.[7]

[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.

[7] In practice, we assume that the size of startups depreciation rate is large enough to guarantee that the

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:

$$\begin{aligned} v_t(z,m) =& max_{y,s,\varsigma} \quad e + \beta \mathbb{E}^{\nu}{}_t v_{t+1}(z',m') \\ e =& y - s\eta(\theta,s)\varsigma - w_t l_p - w_t \frac{\kappa}{2} s^2 \\ & y_{j,t} \leq z_{j,t} l_{j,t} \\ & y_{j,t} \leq m_{j,t} + \mathbb{M}_{j,t} \\ m' =& (1-\delta_n)(m + s\eta(\theta,s)) \\ log(z') =& \rho_z log(z) + \epsilon_z \end{aligned} \tag{8}$$

with $\mu(\theta, s)\varsigma = w_t$, which indicates that startup owners can be indifferent between low upfront-cost VCs and high upfront-cost VCs, if queues in high upfront-cost VCs are sufficiently shorter than in low upfront-cost VCs. All choice variables are non-negative.

Proposition 2: The optimal conditions of VC imply

1. $\theta = \frac{\gamma_m}{1-\gamma_m}\kappa s$
2. $\varsigma = \frac{w}{\xi}\left(\frac{1-\gamma_m}{\gamma_m \kappa}\right)^{1-\nu}\theta^{2-\nu-\gamma_m \nu}$

VC keeps hiring some specialists each period, even when a low productivity realization causes it to contract overall.

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 of households, r_t is the risk-free rate, w_t is the wage rate, B_t^{rf} is one-period risk-free debt, and T_t is 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 $y(S; w,r), s(S; w,r), l(S; w,r)$, $\varsigma(S; w,r), e(S; w,r)$ 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 $\mu(\theta, s)\varsigma = w$ and $\theta > 0$; (3) all markets clear:

Consumption goods market clears. The total consumption should equal total revenue in the economy:

$$C_t = E_t = \int e_t d\phi(S). \tag{11}$$

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

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

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 1:[8]

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

Zero-net supply of the risk-free bond. The aggregate demand for the risk-free bond must equal its supply, which is normalized to zero.

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

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

6.1 Model Calibration

The calibration is summarized in Table 5. 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 which affects VC's valuation and earnings. We calibrate the parameters that govern capital supply: $\rho = 0.85, \sigma = 0.15$ to match the average earnings per capital and the correlation of VC earnings.

The demand for capital from deep-tech startups is sticky and requires some effort from Ph.D. partners to correctly identify deep-tech startups with good potential to invest. This process incurs sufficient search cost, for example, the regular wages that are spent on hiring Ph.D. partners, and some upfront cost, such as cost on screening Deep-Tech from non-deep-tech startups. Every year, some existing deals expire and there are also some new deals that are issued. As a result, invested capital in Deep-Tech is a state variable that has a law of motion. We back out the depreciation rate of invested Deep-Tech capital $\delta = 0.24$ 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 average ratio of new investment to total invested Deep-Tech capital. For γ_m, we set it to 0.6 to match the average ratio of the number of Ph.D partners to the number of Deep-Tech startups invested.

Search friction limits the hiring of Ph.D. partners by increasing the hiring cost measured by the total wage expense on Ph.D. partners. We calibrate κ to 5 to match the average ratio of total wage expense in other employees and total wage expense in Ph.D. partners.

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: $s/(l+s)$, predicts a higher investment rate and a higher VC value. We use the simulation data to estimate the following regression specification:

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

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 6 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 needs 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 6 shows the coefficient estimates of the the inverse of market tightness.

7 Counterfactual Analysis

How does supply of Ph.D. partners in the labor market and the supply of capital to VCs affect their investment in Deep-Tech startups and the equilibrium valuation of VC industry? To answer these questions, in this section, we use the calibrated model to perform counterfactual analysis.

7.1 Supply of Ph.D. Partners and Aggregate Value

In the baseline model, the aggregate labor supply is exogenously set to 1. In the first set of counterfactual analysis, we solve for the equilibrium implied aggregate value of VC and the total investment in Deep-Tech startups relative to non-deep-tech when we change the values of aggregate labor supply from 0.2 to 1.8. Figure 3 plots the aggregate value and the aggregate investment in DeepTech relative to non-deep-tech startups against the aggregate Ph.D. partners in equilibrium. The increasing aggregate value and investment in DeepTech startups suggest that in equilibrium, more supply of Ph.D. partners relax the market frictions and therefore boost more investment in DeepTech startups with relatively higher return and value. In addition, the value increases more rapidly when there are more equilibrium Ph.D. partners. Specifically, when the aggregate Ph.D. partners increase by 10% from baseline value (0.23), the aggregate value of VCs increase by around 19% from 2.22 in the baseline model.

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 investors to evaluate, support, and guide research-intensive ventures.

Despite the advantages of tech-literate investors, our analysis highlights a persistent scarcity of PhD-trained partners in the VC industry, and identifies a geographic variation in market tightness in deep-tech startup funding. While deep-tech startups are highly concentrated in regions like California, the availability of investors with the technical expertise to evaluate and support them is disproportionately low. This imbalance suggests that deep-tech startups in certain regions experience higher funding frictions. To formalize these findings, we develop a structural model that incorporates search and matching frictions, explaining why tech-literate VCs are limited and why the investment process in deep-tech startups faces structural barriers.

Our findings have important implications for policymakers, investors, and entrepreneurs. Efforts to increase the supply of tech-literate VCs could help bridge the funding gap for deep-tech startups. For VC firms, hiring PhD-trained partners could improve investment selection and portfolio outcomes. For deep-tech entrepreneurs, our results emphasize the importance of seeking investors with technology literacy. Overall, this study provides new insights into the relationship between investor expertise and deep-tech funding, highlighting structural frictions in the VC market that warrant further attention in both research and policy discussions.

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Table 1: Summary Statistics

Variable	Count	Min	Q25	Median	Mean	Q75	Max	SD
PhD Partner Ratio	182,405	0	0	0	0.0758	0.0769	1	0.1675
isDeepTech	182,405	0	0	0	0.3219	1	1	0.4672
Year Founded	182,405	2000	2013	2016	2015.52	2019	2023	4.73
Founders with PhD	182,405	0	0	0	0.198	0	1	0.3982
Closed Startups	182,405	0	0	0	3.20	0	100	17.59
Mergers	182,405	0	0	0	14.93	0	100	35.64
IPOs	182,405	0	0	0	4.37	0	100	20.45
Mergers + IPOs	182,405	0	0	0	17.69	0	100	38.16

Notes: This table reports summary statistics for key variables at investor-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 Investor Ratios by State

State	DT Company Count	DT Investor 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) companies by state in 2022, along with the DT Investor Ratio and DT Company Ratio. The DT Investor Ratio represents the proportion of investors with at least one PhD partner as a share of the total number of investors 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	-0.1218		
	(0.1608)		
PhD.Ratio × isDeepTech	0.6369***	0.6438***	0.5505***
	(0.1334)	(0.1363)	(0.0014)
Investor FE	Y	Y	Y
Year FE	Y	Y	Y
Company FE	Y	Y	Y
VC×Year FE		Y	
VC×Year ×Market FE			Y
Observations	13,634,510	13,630,437	13,594,865
R^2	0.2173	0.2170	0.1809

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 investor fixed effects, year fixed effects, and company fixed effects. Column (2) further adds VC-year fixed effects, while Column (3) includes VC-year-state-industry fixed effects. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 4: Investment Performance

	Close (1)	**M&A** (2)	**IPO** (3)	**M&A and IPO** (4)
isDeepTech	-1.442***	-5.349***	5.384***	-1.524***
	(0.1542)	(0.3557)	(0.3370)	(0.3418)
isDeepTech × PhD.Ratio	-3.431***	-0.2193	8.775***	7.319***
	(1.140)	(1.802)	(1.893)	(1.918)
Controls	Y	Y	Y	Y
VC×Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	182,405	182,405	182,405	182,405
R^2	0.32053	0.41977	0.50404	0.45823

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. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Model Calibration

Parameter	Value	Moments	Data	Model
ρ	0.85	Earnings Correlation	0.8	0.83
σ	0.15	Earnings/Capital	0.22	0.23
δ	0.24	Average capital growth	0.25	0.24
γ_m	0.6	# of Ph.D./# of Startups	0.66	0.62
ξ	0.25	Average new investment to existing capital	0.33	0.32
κ	5	$\frac{\text{Wage expense on other labor}}{\text{Wage expense on Ph.D. partners}}$	3.7	3.2
β	0.97	Annual risk-free rate	3%	3%

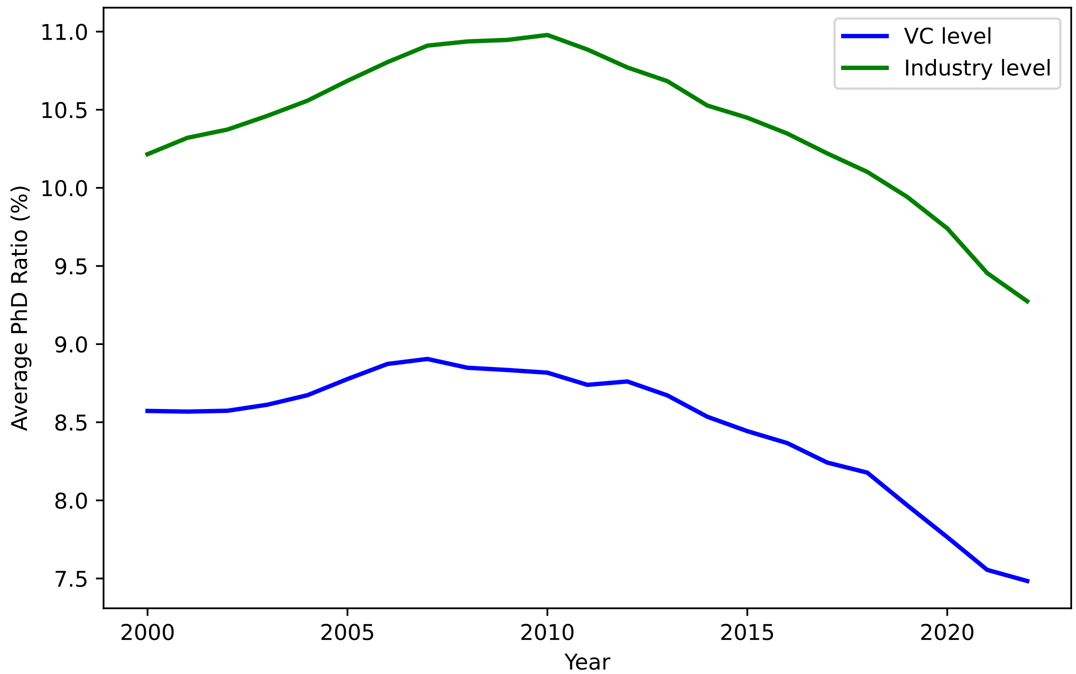
Notes: This table reports the values of calibrated parameters in the model and the matched moments in the data and model.

Table 6: Model Implication

	Investment Rate	Matched Rate	IRR (%)
		Panel A	
Labor Share	0.44	0.59	5.56
		Panel B	
Market Tightness	0.10	0.12	5.72

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 the inverse of market tightness, defined as the ratio of Ph.D. partners to startups, on VCs' investment and return.

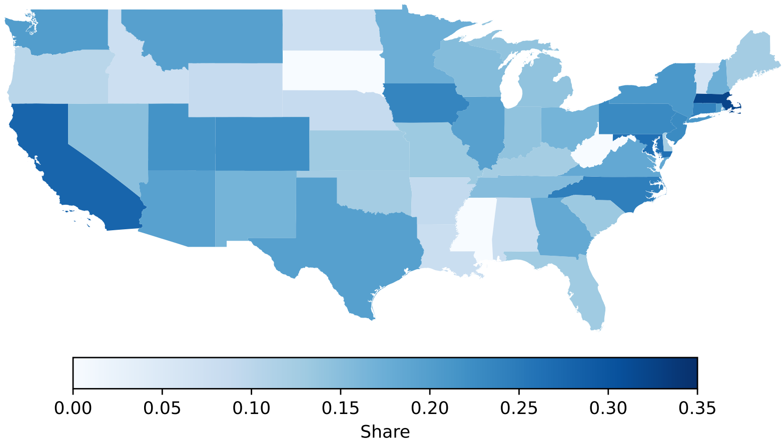
Figure 1: PhD in the VC Industry



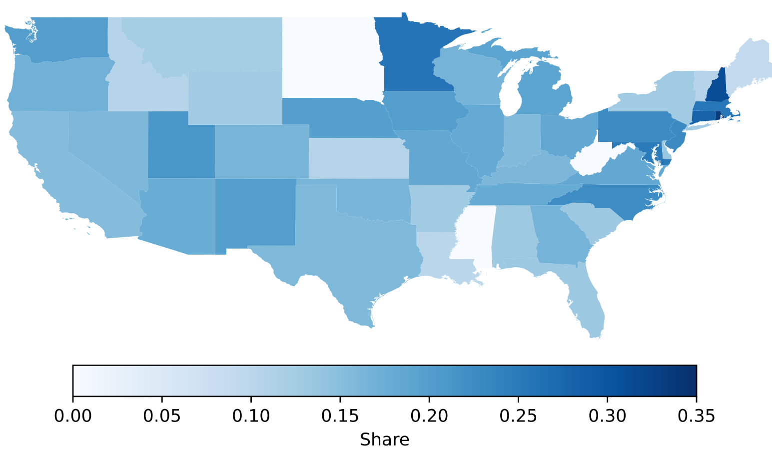
Notes: This figure plots the ratio of PhD partners in the VC industry. The green line represents the overall share of PhD partners among all VC partners in the industry. It is calculated as the total number of PhD partners divided by the total number of partners in the VC industry for each year. The 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 Investors

(a) Share of Deep-Tech Startups

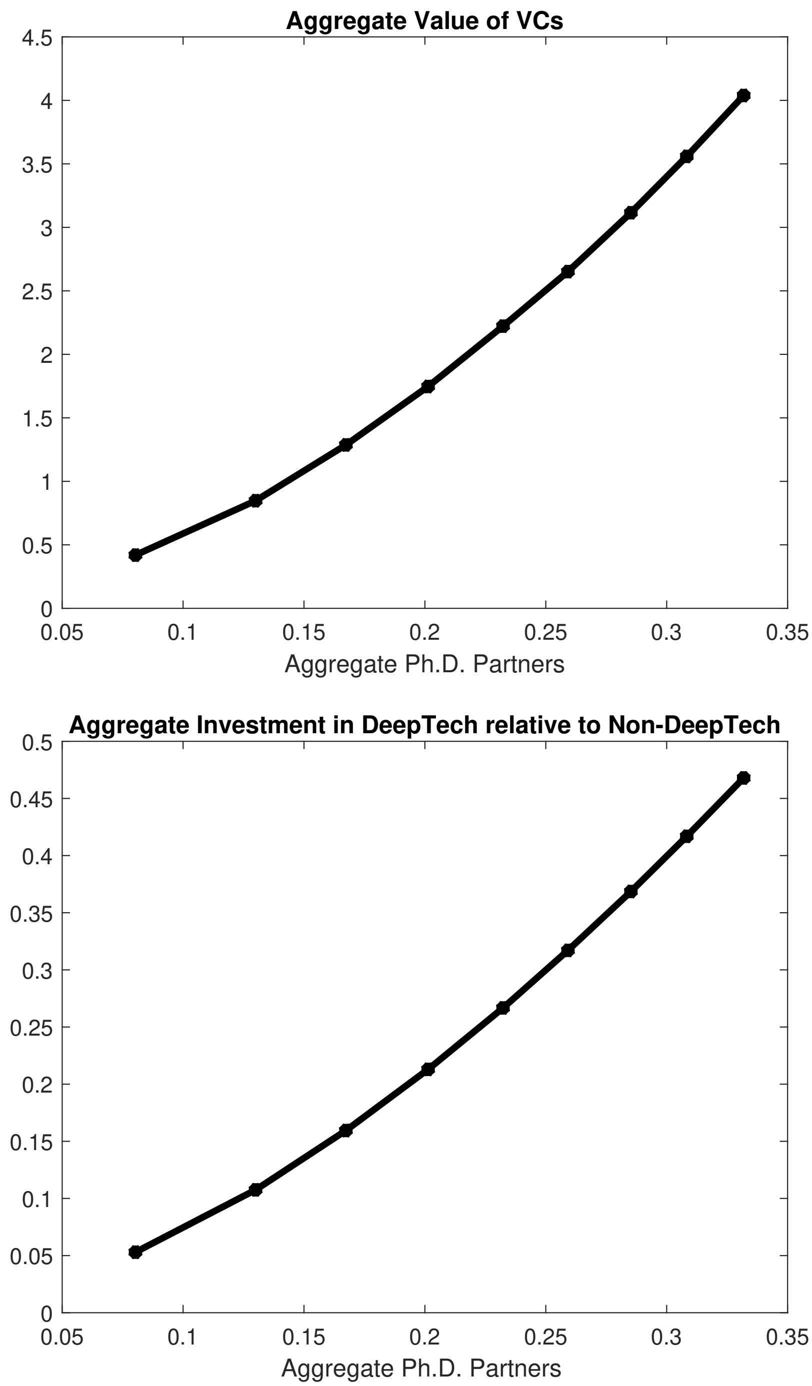


(b) Share of Investors with PhD Partner(s)



Notes: This table reports the ratio of Deep-Tech (DT) companies along with the DT Investor Ratio and DT Company Ratio by state across years. The median is used when aggregating data from the state-year level to the state level. The DT Investor Ratio represents the proportion of investors with at least one PhD partner as a share of the total number of investors who made investments in the state that year. The DT Company Ratio reflects the share of Deep-Tech companies relative to all startups that received funding in the state during the same period. 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 Effects of Labor Supply



Notes: This figure plots the aggregate value and the aggregate investment in DeepTech relative to non-deep-tech startups against the aggregate Ph.D. partners in model equilibrium when we exogenously vary aggregate labor supply from 0.2 to 1.8.

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 4. 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.

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 Patners' Highest Degree

Panel A: Bachelor	
Major Concentration	Count
Economics	814
Computer Science	399
Business Administration	360
Finance	352
Political Science	168
Panel B: Master	
Major Concentration	Count
Finance	945
Computer Science	354
Business	310
Management	276
Business Administration	263
Panel C: PhD	
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)
Investor FE	Y	Y	Y
Year FE	Y	Y	Y
Company FE	Y	Y	Y
Investor×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 investor 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)
Investor×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. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.