Financing or Producing Innovation? The Allocation of Scientific Human Capital*

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July 2026

Abstract

This paper studies how the allocation of scientific human capital between innovation financiers and producers shapes industry profitability. We use the venture capital (VC) industry as a setting. By matching PitchBook with Revelio Labs, we document three facts: (1) scientific human capital in VC is declining and geographically uneven; (2) investors with more Ph.D.-trained partners finance more profitable deep-tech deals; and (3) shocks that reallocate Ph.D. partners toward founders raise VC industry profitability. A dynamic search-and-matching model rationalizes these facts: Ph.D. partners expand the supply of funding but divert limited talents from profitable producers who demand it, generating a hump-shaped relationship between the Ph.D. partners and aggregate VC profitability. The model calibration helps explain the persistently declining share of Ph.D. partners in the VC industry.

Keywords: Scientific Human Capital; Venture Capital; Financing Innovation; Labor Reallocation

*We thank Jack Xiaoyong Fu (discussant), Juanita González-Uribe, Leonid Kogan, Ramana Nanda, Dimitris Papanikolaou, and seminar participants at the Wabash River Finance Conference, Chicago Entrepreneurial Finance Workshop, CityU International Finance Conference, CES NA Annual Conference, and Helsinki Finance Summit for their valuable comments and suggestions. We are grateful for financial support from the Gies College of Business. All errors are our own.

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1 Introduction

Scientific human capital is an important input in the production and commercialization of innovation. Frontier innovation often requires specialized knowledge to evaluate and bring to market. Yet the individuals who possess this expertise face competing occupational uses of their skills. They can apply scientific knowledge directly by founding or joining startups, or they can help allocate resources to innovation by evaluating, financing, and advising technology startups. The allocation of scientific human capital across these roles may therefore shape not only who produces innovation, but also which innovations receive funding.

This paper studies the allocation of scientific human capital between financing and producing innovation. We focus on Ph.D.-trained individuals because doctoral training provides a measurable proxy for the stock of scientific human capital. Our setting is the venture capital (VC) industry, where scientific expertise may be valuable not only to startups (innovation producers), but also to financial intermediaries (innovation financiers) that screen and select them. Ph.D.-trained individuals make occupational choices between becoming VC partners, who can improve the evaluation of startups whose value depends on frontier innovation, and founding startups seeking VC financing. Because scientific human capital is limited, its allocation between financing and producing innovation is critical for innovation activity and VC profitability in the economy.

We examine the allocation effects of scientific human capital using new matched data from PitchBook and Revelio Labs. PitchBook provides financing rounds, investor characteristics, and startup outcomes. Revelio Labs provides individual career histories, education records, and job postings, which allow us to measure the share of Ph.D.-trained partners within VC firms and to identify deep-tech startups based on their demand for advanced scientific labor. Combining these data lets us study both the supply and demand sides of the innovation market.

The empirical analysis documents three facts. First, scientific human capital allocated to VC firms is declining and geographically uneven. The number and share of VC-backed deep-tech startups have increased over time, suggesting rising demand for investors capable of evaluating scientifically complex opportunities. Over the same period, the share of Ph.D.-trained partners in the VC industry has declined. The geographic distribution is also uneven: some regions have many deep-tech startups but relatively few VC investors with Ph.D.-trained partners, while others have a larger concentration of scientific human capital on the financing side.

Second, VC firms with more scientific human capital are more likely to select and

finance better-performing deep-tech startups. Using a matched sample of realized and counterfactual VC-startup pairs, we find that a 10 percentage-point increase in a VC firm's Ph.D. partner ratio raises the probability of investing in a deep-tech startup by 0.078 percentage points, or 3.9% relative to the matched-sample baseline. Among realized investments, a 10 percentage-point increase in the Ph.D. partner ratio reduces the failure probability of deep-tech startups by 0.424 percentage points and raises the probability of an M&A or IPO exit by 0.934 percentage points, relative to non-deep-tech startups. The instrumental-variable estimates are consistent with the OLS estimates on the effect of scientific human capital on deep-tech investment.

Third, reallocating scientific human capital from VC firms toward entrepreneurship can improve venture-sector performance. We use state-level variation in non-compete enforcement as an exogenous shock to the non-wage incentive of VC partnership. Stronger non-compete enforcement, which implies less labor mobility and a lower value of the outside option within the same industry, is associated with more transitions from Ph.D.-trained VC partners into founder roles and a lower ratio of Ph.D.-trained partners to Ph.D.-trained founders. VC profitability improves following these shocks. These results show that the reallocation of scientific human capital between VC firms and entrepreneurship shapes the aggregate profitability of the VC sector.

To interpret these empirical findings and assess their implications for capital allocation efficiency, we develop a dynamic structural model of VC–startup matching with directed search, following the canonical framework of Gourio and Rudanko (2014). VC firms are heterogeneous in productivity and employ two types of labor: general staff, who process investment deals, and technical specialists—modeled as Ph.D.-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 aggregate supply of highly skilled technical talent. Ph.D.-trained partners play a key role in identifying profitable startups in a frictional market. Households supply labor, and in each period they make an occupational choice by comparing the expected payoff from creating startups as founders with the total return from working as Ph.D. partners for VC firms.

In each period, VC firms compete for investment opportunities in profitable startups by offering them a one-time bonus and generating revenue from successful investments. Their revenue is determined by two primary factors. First, capital supply—defined as a VC firm's capacity to process investment deals—is determined by an exogenous productivity shock and the firm's employment of regular workers who handle transactions. Second, capital demand is constrained by the number of deep-tech startups that Ph.D.-trained partners successfully identify and match with. The VC revenue function captures the com-

plementarity between capital supply and capital demand. Investment relationships are formed through a constant returns-to-scale matching function, in which the probability of matching depends on the equilibrium ratio of Ph.D.-trained partners to startups.[1] The investment relationship is sticky and subject to a constant depreciation rate, which makes it a long-term capital.

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

A central question is how the reallocation of scientific human capital affects the aggregate value of the VC sector. Specifically, does an increase in the equilibrium number of Ph.D.-trained partners raise the overall value created by VC firms? To address this question, we examine how equilibrium labor allocation and aggregate VC value respond to changes in the non-wage incentive of becoming a Ph.D.-trained partner, denoted by Δ, in the indifference condition of households' occupational choice problem. A higher value of Δ makes partnership positions relatively more attractive, thereby endogenously increasing the equilibrium number of Ph.D.-trained partners. We solve for steady-state equilibrium under different values of Δ.

The quantitative results reveal a hump-shaped relationship between Δ and the aggregate value generated by the VC sector. An increase in Δ initially raises the number of Ph.D.-trained partners, enhancing VC firms' ability to identify, evaluate, and finance profitable deep-tech startups. However, as Δ continues to rise, fewer households choose to become startup founders, reducing the pool of potential deep-tech ventures and, consequently, the demand for VC funding. These opposing forces—an increasing equilibrium number of Ph.D.-trained partners and a declining equilibrium number of deep-tech startups—generate a hump-shaped pattern in both new investment and aggregate VC value over Δ.

This mechanism provides insight into the persistently low and declining presence of Ph.D.-trained partners in VC firms. When the initial value of Δ is sufficiently high, the economy contains too few startups relative to Ph.D.-trained partners, reducing the marginal utility of hiring additional partners for the VC sector. In such an environment, VC firms have little incentive to hire more Ph.D.-trained partners. As a result, the econ-

[1] The ratio of Ph.D.-trained partners to startups captures the imbalance between the number of deep-tech startups seeking funding and the availability of tech-literate VC firms.

omy can remain in an equilibrium characterized by a structurally low level of technical expertise among investors. In the baseline calibration, the estimated value of Δ lies in the downward-sloping portion of the hump-shaped value curve, implying that a further increase in the equilibrium number of Ph.D.-trained partners would reduce, rather than increase, the aggregate value of VC.

To perform an analysis analogous to a tightening of non-compete agreements, which reduces the non-wage incentive to become a Ph.D.-trained partner, we introduce a negative shock to Δ. This shock represents a decline in the non-wage incentive associated with VC partnership and therefore lowers the equilibrium ratio of Ph.D.-trained partners to startups. The numerical experiment suggests that a reduction in this ratio increases the aggregate value of the VC sector.

Finally, we use the calibrated model to evaluate geographic heterogeneity in market structure across four major VC hubs: California, Massachusetts, New York, and Texas. Texas and New York exhibit ratios of Ph.D.-trained partners to deep-tech startups that are close to the value-maximizing level, placing them near the peak of the hump-shaped aggregate value curve. Massachusetts has the highest ratio of Ph.D.-trained partners—approximately 61% higher than that of Texas—placing it further along the declining portion of the curve. California also lies on the downward-sloping side of the hump-shaped relationship, implying that reducing, rather than increasing, the equilibrium number of Ph.D.-trained partners would raise aggregate VC value. These findings help explain the persistently low and declining presence of Ph.D.-trained partners in VC firms. More broadly, the geographic heterogeneity in equilibrium labor allocation highlights the importance of local labor-market conditions and regulations, suggesting that location-based policies may be more effective than uniform national interventions.

This research contributes to three streams of literature. First, it adds to the body of work on financing innovation. A large literature studies the *financing* of innovation: prior studies establish the role of capital in funding innovative startups (Kerr and Nanda, 2015; Lerner and Nanda, 2020) and show that financing conditions shape innovation and entrepreneurial entry (Howell, 2017; Babina, 2020). Beyond the quantity of capital, a growing literature shows that financing innovation also depends on financier *specialization* and expertise: specialized venture capitalists succeed more often, whereas generalists underperform through both poor selection within industries and inefficient allocation of funding across them (Gompers, Kovner, and Lerner, 2009); investor human capital drives value-adding intermediation (Bottazzi, Da Rin, and Hellmann, 2008); and intermediaries' specialized expertise shapes which firms they finance (Paravisini, Rappoport, and Schnabl, 2023). More recently, a strand of this literature emphasizes startups as innovation *pro-*

ducers, showing that unlisted firms are "quietly ahead" of stock market-listed firms in the innovation race and increasingly stay private longer (Bias and Ljungqvist, 2026; Ewens and Farre-Mensa, 2020). We connect these two sides. Whereas the specialization literature takes expert talent as fixed within the financier, we show that scientific human capital is two-sided: it can screen and finance innovation or produce it directly. We show that how this limited talent is allocated between producing and financing innovation shapes the flow of capital to innovation and the profitability of the venture sector.

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. Related work shows that VC investors shape startup outcomes through screening, monitoring, and the resolution of information frictions (Bernstein, Giroud, and Townsend, 2016; Howell, 2020; Howell, Lerner, Nanda, and Townsend, 2020). 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 technology sectors where both specialized expertise and recruitment challenges play a critical role in capital allocation. This paper is 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 that examines how labor mobility affects corporate innovation by changing outside options and the incentives of key talent (Gao, Wang, and Wu, 2024). Previous studies generally find that increased labor mobility and retention costs reduce corporate innovation and growth (Eisfeldt and Papanikolaou, 2013; Shi, 2023; Chen, Zhang, and Zhang, 2023), with one exception documenting nonlinear effects (Chen, Li, Thakor, and Ward, 2026). Related work also shows that firms' innovation choices shape employee retention (Ma, Wang, and Wu, 2023). Our paper adds to this literature by proposing a new perspective on labor reallocation in corporate innovation: limited mobility of innovation financiers can increase innovation production in the economy.

More broadly, we speak to the literature on internal capital markets and the allocation of resources across projects. A central insight of this literature is that financiers can create value by reallocating scarce resources toward higher-value projects, but may also generate distortions when allocation is affected by agency problems, influence costs, or organizational frictions (Stein, 1997; Scharfstein and Stein, 2000; Ozbas and Scharfstein, 2010; Matvos and Seru, 2014; Dai, Giroud, Jiang, and Wang, 2024). We extend this logic from the allocation of capital within firms to the allocation of scientific human capital across

firms and roles. The relevant trade-off is not only which projects receive capital, but also whether scientifically trained workers should evaluate and finance innovation or produce it directly.

The rest of the paper proceeds as follows. Section 2 describes the data and key measures. Section 3 presents the empirical facts. Section 4 develops and calibrates the dynamic model. Section 5 concludes.

2 Data and Measures

2.1 Data

Startup and Investment Data We construct our dataset using PitchBook, a leading database on VC deals that provides detailed information on financing rounds, investor characteristics, and firm performance metrics. PitchBook is owned by Morningstar and is increasingly used in venture capital research because it provides broad coverage of startup financing deals. Our sample includes all U.S.-headquartered firms founded between 2000 and 2023 in PitchBook data as of February 2025. We then 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). We investigate only U.S.-headquartered VC firms because their human capital data are the most comprehensive.

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 identify Ph.D.-trained partners within VC firms and study their engagement with deep-tech startups. The data consist 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. These postings are 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. We use these postings to identify deep-tech startups based on their demand for scientific human capital. For our analysis, we focus on job postings located in the U.S., 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 A1. 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.

2.2 Key Measures

Scientific Human Capital We measure scientific human capital using individuals who hold a Ph.D. degree. As doctoral training represents a substantial investment in scientific and technical expertise, it provides a natural proxy for scientific human capital. To examine the allocation of scientific human capital to the VC industry, we focus on VC partners. A partner is defined broadly to include any individual with a job title containing "partner," "founder," "angel," "owner," "advisory board member," or "executive." Using partners' employment histories, including their start and end dates at each firm, we calculate the share of partners holding a Ph.D. degree for each VC firm-year. This measure captures the

allocation of scientific human capital within VC firms.

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 Ph.D. or MD (hereafter referred to as Ph.D.) 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 Ph.D. 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 Ph.D. degree. Based on this criterion, 16% of the sample is identified as deep-tech startups.

The final analysis sample includes 208,684 VC-startup deal observations. Table 1 presents summary statistics for the key variables used in the analysis, measured at the VC-startup-deal level. The majority of VC firms in these deals do not have any Ph.D.-holding partners, as reflected by the median Ph.D. partner ratio of zero. The average Ph.D. partner ratio is 8%. In the sample, 32% of VC-startup-deal observations involve deep-tech startups.[2] Regarding exit performance, 3.4% of deal observations involve startups that eventually close, go out of business, or enter bankruptcy. Meanwhile, 14.1% involve startups that exit through mergers or acquisitions, and 5.1% involve startups that successfully go public.

3 Stylized Facts

3.1 Fact 1: Declining scientific human capital in the VC industry and geographic variation

We begin by documenting several stylized facts about the allocation of scientific human capital in the innovation ecosystem. We first document a growing demand for funding among deep-tech startups, alongside a declining allocation of scientific human capital to the financing side of innovation. The number of deep-tech startups increases substantially over time, and investment activity associated with these firms rises alongside it. As shown in Figure 1, both the number and share of deep-tech investments have increased steadily over the sample period. Moreover, as per Table **??**, deep-tech startups require scientific

[2] At the startup level, 18.9% of firms are classified as deep-tech, whereas at the VC-deal level, 32.0% of observations involve deep-tech startups.

human capital to invest. These patterns suggest a growing demand for investors capable of evaluating and financing deep-tech startups.

Despite the growing demand for scientific expertise in screening technology startups, the share of Ph.D. partners in the VC industry declines over the same period. Table 1 highlights the low ratio of Ph.D. partners in VC firms. Figure 2 further supports this observation. The green line represents the industry-wide share of Ph.D. partners among all VC partners, while the blue line shows the average Ph.D. ratio at the firm level. Both lines show a similar trend: the share of Ph.D. partners has declined noticeably since 2010, indicating an increasing scarcity of Ph.D. partners in the industry. This downward trend suggests that, despite the growing trend of deep-tech investments, the supply of VCs with scientific human capital is not keeping pace with investment needs.

Allocating scientific human capital into 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 Ph.D.-trained professionals enter the industry at early career stages, limiting the pipeline of candidates who can advance to partner positions. Table A2 provides insights into the educational background of individuals working in the VC industry, along with the proportion of Ph.D. holders in each major field. The majority of VC professionals hold degrees in Business, yet only 0.78% of them have a Ph.D. degree. While Biology exhibits the highest Ph.D. ratio, it represents only a small fraction of the overall VC workforce, further underscoring the limited presence of Ph.D.-trained professionals in the industry.

Moreover, lateral hiring from other VC firms is constrained by the already low supply of Ph.D. partners. Table A3 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 Ph.D. in each field. This scarcity of Ph.D.-trained partners limits the ability of VC firms to recruit scientifically trained talent from competitors and expand their stock of scientific human capital through external hiring.

Beyond aggregate hiring frictions among VC firms, the geographic allocation of scientific human capital on the financing side is highly uneven. Table 2 reports investor characteristics across major VC states, including the average deep-tech investment propensity, Ph.D. partner counts, deal activity, and measures of Ph.D. partner intensity. California has by far the largest number of active investors, with 1,738 investors, and also exhibits a high average deep-tech investment indicator of 0.46. However, its average Ph.D. partner count is only 0.64, and its Ph.D. partner share is 0.13. By contrast, Massachusetts has fewer investors, with 266, but a much higher average Ph.D. partner count of 1.24 and a

Ph.D. partner share of 0.15, despite a slightly lower average deep-tech investment indicator of 0.43. New York has a comparable deep-tech investment indicator to Massachusetts, at 0.44, but a substantially lower average Ph.D. partner count of 0.36 and Ph.D. partner share of 0.07. These differences suggest that the availability of scientific human capital among VC investors varies substantially across states, even among states with active deep-tech investment markets.

Figure 3 further illustrates this geographic disparity by mapping the ratio of deep-tech startups and the proportion of VCs with Ph.D. partners across different states. The figure reinforces the finding that the distribution of deep-tech startups does not fully align with the distribution of scientific human capital within VC. While California has a relatively high concentration of deep-tech startups, it does not exhibit a correspondingly high proportion of VCs with Ph.D. partners. This figure reveals substantial geographic variation in the allocation of scientific human capital between producing innovation and financing innovation. Some regions allocate a relatively larger share of scientific talent to entrepreneurial activity, while others allocate more scientific talent to VC firms.

Taken together, these findings reveal a growing imbalance in the allocation of scientific human capital within the innovation ecosystem. While the demand for funding among deep-tech startups has expanded rapidly, the share of scientific human capital allocated to financing those startups has declined and remains unevenly distributed across regions. The geographic evidence further suggests substantial variation in how scientific human capital is allocated between producing innovation and financing innovation. As a result, local markets differ in the availability of scientifically trained investors relative to deep-tech entrepreneurial activity.

3.2 Fact 2: Ph.D.-trained financiers better match with deep-tech startups

The previous section shows that scientific human capital allocated to VC firms is unevenly distributed. We next examine how scientific human capital affects investment decisions within VC firms. Specifically, we ask whether VC firms with a higher share of Ph.D.-trained partners are more likely to invest in deep-tech startups and whether those investments generate better outcomes.

The allocation of scientific human capital to VC firms may be particularly important in deep-tech sectors. Unlike conventional startups, deep-tech ventures often rely on scientific discoveries and highly specialized technologies whose commercial potential is difficult to evaluate. As a result, investors face greater screening and information frictions when assessing deep-tech opportunities. Scientific human capital may help alleviate these fric-

tions by improving investors' ability to understand underlying technologies, distinguish promising innovations from weaker projects, and identify startups with greater commercialization potential. If so, VC firms with a larger concentration of scientific human capital should be more likely to invest in deep-tech startups and achieve better investment outcomes.

We first examine whether VC firms with greater scientific human capital are more likely to finance deep-tech startups. PitchBook observes realized VC-startup matches, but not the startups each investor considered and rejected. Estimating investment choice, therefore, requires a feasible choice set that combines actual deals with plausible non-investment alternatives.

Following Gompers, Mukharlyamov, and Xuan (2016) and Hegde and Tumlinson (2014), we construct counterfactual pairs by identifying, for each year t, VC firms actively making investments and startups actively seeking funding. A VC firm is active if it participates in at least one deal in year t. A startup is active if it raises funding or goes bankrupt in year t, since both outcomes indicate that the firm was in the financing market.

We then match VCs to startups using observed investment preferences: location (state), industry, and development stage (seed, early VC, and late VC rounds). These restrictions keep the counterfactuals close to opportunities an investor could realistically evaluate. The 208,684 realized VC deals generate 10,862,927 VC-startup pairs after adding these counterfactual opportunities.

The regression specification is

$$\text{Invest}_{ijt} = \beta_1(\text{Ph.D. Ratio}_{jt} \times \text{isDeepTech}_i) + \eta_{it} + \eta_{jt} + \varepsilon_{ijt} \tag{1}$$

where Invest_{ijt} records whether VC j invests in startup i in year t. Ph.D. Ratio_{jt} is the share of partners in VC firm j with Ph.D. training, and isDeepTech_i indicates whether startup i is classified as deep-tech.

The interaction $(\text{Ph.D. Ratio}_{jt} \times \text{isDeepTech}_i)$ measures whether Ph.D.-intensive VC firms tilt their investment toward deep-tech startups, relative to non-deep-tech startups. Table 3 reports several fixed-effect specifications. Standard errors are clustered at the VC level.

Columns (1) and (2) present OLS estimates. In Column (1), which includes company-by-year fixed effects, the interaction coefficient is positive and statistically different from zero. A 10 percentage-point increase in the share of Ph.D.-trained partners is associated with a 0.078 percentage-point increase in the probability of investing in a deep-tech startup. Relative to an average investment probability of about 2.0% in the matched sam-

ple, this is a 3.9% increase. The coefficient on Ph.D. Ratio is negative and statistically insignificant, so the pattern does not reflect a general increase in investment propensity for all startups.

Column (2) adds VC-by-state-by-year fixed effects. This specification compares choices made by the same VC in the same state and year across deep-tech and non-deep-tech startups. The coefficient remains positive, which rules out explanations based on time-varying VC activity, local investment conditions, or state-specific investment strategies. Across the OLS specifications, VC firms with greater scientific human capital allocate relatively more capital to deep-tech opportunities.

The main identification concern is endogenous partner composition. VC firms may hire Ph.D.-trained partners when they plan to expand into technology-intensive sectors, or unobserved changes in investment strategy may affect both partner composition and portfolio choice. VCs with existing deep-tech strategies may also recruit technically trained partners to support those investments. In each case, the concentration of scientific human capital within a VC firm would be correlated with deep-tech investment without necessarily causing it.

To address this concern, we instrument a VC firm's Ph.D. partner ratio using the lagged Ph.D. partner ratio of peer VC firms investing in the same industry but located in different states. Relevance comes from common industry demand for technical expertise and shared labor-market conditions for Ph.D.-trained investors. The exclusion restriction is that the Ph.D. composition of out-of-state peer investors affects the focal VC's investment decisions only through the focal VC's own partner composition. Lagging peer composition reduces simultaneity concerns, while company-by-year fixed effects absorb startup-level investment demand and shocks common to investors evaluating the same company.

Columns (3) and (4) report the second-stage IV estimates. The first-stage F-statistics are 40.1 and 64.6, respectively. The IV coefficients are larger than the OLS estimates, suggesting that OLS may understate the effect of scientific human capital within VC firms on deep-tech investment. In Column (3), a 10-percentage-point increase in the Ph.D. partner ratio raises the probability of investing in a deep-tech startup by 0.379 percentage points. Column (4), which adds VC-by-state-by-year fixed effects, gives a smaller but still positive estimate of 0.228 percentage points. The negative coefficient on Ph.D. Ratio in Column (3) indicates that VC firms with a higher share of Ph.D. partners are less likely to invest in non-deep-tech startups, consistent with a reallocation of investment toward deep-tech startups.

Another way to examine the question is to compare deals within the same VC: are deals led by Ph.D. partners more likely to involve deep-tech startups than deals led by non-Ph.D.

partners? Table A5 shows that, within the same VC and year, a deal led by a Ph.D. partner is about 8 percentage points more likely to back a deep-tech startup than a deal led by a non-Ph.D. partner. This finding provides partner-level evidence that complements the VC-level results.

Taken together, the estimates show that VC firms with higher Ph.D. ratios are more likely to invest in deep-tech startups. The evidence suggests that scientifically trained investors possess an advantage in evaluating and selecting deep-tech startups.

To examine whether scientific human capital also affects investment outcomes, we restrict the sample to realized investments and estimate:

$$\text{Performance}_{ijt} = \beta_1 \,\text{isDeepTech}_i + \beta_2(\text{Ph.D. Ratio}_{jt} \times \text{isDeepTech}_i) + \gamma X_{it} + \eta_{jt} + \varepsilon_{ijt} \tag{2}$$

where Performance_{ijt} is the exit outcome of startup i after receiving investment from VC j in year t. Outcomes include failure, acquisition, and IPO. The controls in X_{it} include whether the founder has a Ph.D., deal type, founding year, state of incorporation, and industry-year fixed effects. VC-year fixed effects absorb unobserved changes in investor quality or strategy over time. The coefficient β_2 tests whether VCs with a higher Ph.D. partner ratio generate better outcomes for deep-tech startups relative to non-deep-tech startups.

Columns (1) and (2) present OLS estimates. In Column (1), the dependent variable is startup failure. The coefficient on (Ph.D. Ratio $\times$ isDeepTech) is negative and statistically different from zero. A 10-percentage-point increase in a VC firm's Ph.D. partner ratio reduces the failure probability of deep-tech startups by 0.424 percentage points relative to non-deep-tech startups. Given an average failure rate of 5.7%, this corresponds to a relative decline of about 7.4%. This result suggests that scientific human capital within VC firms improves the selection and evaluation of deep-tech ventures, leading to lower failure rates among funded startups.

Column (2) examines successful exits, defined as either M&A or IPO. The interaction coefficient is positive and statistically significant. A 10-percentage-point increase in the Ph.D. partner ratio is associated with a 0.934 percentage-point increase in the probability that a deep-tech startup exits through M&A or IPO relative to non-deep-tech startups. VC firms with greater scientific human capital are therefore associated with stronger exit outcomes for deep-tech ventures.

The coefficient on isDeepTech captures the performance difference between deep-tech and non-deep-tech startups when the investing VC has no Ph.D.-trained partners. Across the OLS specifications, deep-tech startups are less likely to fail, but also less likely to exit

through M&A or IPO. This pattern suggests that VC firms without Ph.D.-trained partners may selectively invest in less risky deep-tech ventures, avoiding projects with greater technological uncertainty. Such behavior is consistent with information frictions in deep-tech investing, where limited scientific expertise makes it more difficult to evaluate and screen deep-tech startups.

The same endogeneity concern applies to performance. VC firms may hire Ph.D.-trained partners in anticipation of investing in stronger deep-tech opportunities, or unobserved strategy changes may affect both partner composition and portfolio outcomes. We therefore use the same instrumental-variable strategy, instrumenting the VC firm's Ph.D. partner ratio with the lagged Ph.D. partner ratio of out-of-state peer VCs investing in the same industry.

Columns (3) and (4) report the second-stage IV estimates. The first-stage F-statistic is 104.1 in both specifications. The IV estimates are larger than the corresponding OLS estimates. In Column (3), a 10-percentage-point increase in the Ph.D. partner ratio reduces the failure probability of deep-tech startups by 1.186 percentage points relative to non-deep-tech startups. In Column (4), the same increase raises the probability of an M&A or IPO exit by 3.280 percentage points. These effects are large relative to the baseline rates.

The evidence indicates that deep-tech startups selected by VC firms with a higher share of Ph.D.-trained partners perform better. These startups are less likely to fail and more likely to achieve successful exits. The results survive VC-by-year and industry-by-year fixed effects and are stronger in the IV specifications. Combined with the earlier finding that VC firms with more Ph.D.-trained partners are more likely to invest in deep-tech ventures, the evidence suggests that scientific human capital improves the screening of deep-tech startups. VC firms with more Ph.D.-trained partners not only match with more deep-tech startups, but also select higher-quality deep-tech ventures.

Robusness Checks Table A6 and Table A7 presents robustness checks showing that the investment and performance results are robust to alternative measures of STEM human capital. Specifically, we obtain similar results when using (i) the share of partners with STEM Ph.D. degrees, (ii) the share of partners with at least a STEM master's or Ph.D. degree, and (iii) the share of all employees with at least a STEM master's or Ph.D. degree.

Another potential concern is that the estimated effect of the Ph.D. partner ratio reflects industry specialization rather than scientific human capital per se. Ph.D.-trained partners may be concentrated in technology-intensive sectors such as biotech, advanced materials, or semiconductors, and VCs with such partners may invest more often or more successfully in those sectors because of accumulated specialization, networks, or sector-specific

experience. If so, the estimated relationship could be driven by sectoral focus rather than by technical expertise per se. Table A8 and Table A9 report robustness checks showing that the stylized facts are not driven by VC industry specialization. The tests exclude investments in each VC's most frequently invested industries and show that VCs with more Ph.D.-trained partners remain more likely to invest in deep-tech startups, with stronger performance among those startups.

3.3 Fact 3: Reallocating Ph.D. from financing to producing innovation increases VC profitability

The previous section shows that VC firms with more Ph.D.-trained partners are better able to match with and select high-quality deep-tech startups. However, these findings do not imply that allocating more scientific human capital to VC firms necessarily improves aggregate outcomes. Because Ph.D.-trained individuals can also contribute to innovation as startup founders, there is a tradeoff between financing innovation and producing innovation. We therefore examine whether reallocating Ph.D. talent toward entrepreneurship affects venture ecosystem performance.

To study this question, we require a source of variation that shifts Ph.D.-trained individuals between investor and founder roles. Conceptually, such a shock should reduce the attractiveness of becoming a VC partner relative to becoming a startup founder, thereby inducing some scientific human capital to move from financing innovation to producing innovation. Building on the labor-mobility channel in Chen et al. (2026), we use variation in state-level non-compete enforcement, measured by the Non-Compete Enforcement Index (NCEI), as a shock to the relative attractiveness of VC firms versus entrepreneurship. Stronger non-compete enforcement reduces the value of the outside option associated with VC partner careers, making VC firms relatively less attractive for Ph.D. individuals and increasing the likelihood that they pursue entrepreneurial opportunities instead.

Table 5 shows that stronger non-compete enforcement is associated with a higher probability that Ph.D. partners transition into founding roles. Consistent with this reallocation channel, the ratio of Ph.D. partners to Ph.D. founders declines when year fixed effects are included. These results suggest that non-compete tightening changes the occupational allocation of scientific human capital, shifting Ph.D.-trained individuals away from VC firms and toward entrepreneurship.

We then ask whether this reallocation affects VC profitability. To trace the dynamic

response, we estimate the following local projection specification:

$$Y_{i,t+h} = \alpha_i + \lambda_t + \beta_h \text{NCEI}_{s(i),t} + \varepsilon_{i,t+h}, \qquad h = 0,1,\ldots,7. \tag{3}$$

Here, $Y_{i,t+h}$ denotes VC performance for fund or investor i at horizon h, measured using profitability outcomes such as internal rate of return (IRR) and distributed-to-paid-in capital (DPI) relative to benchmark returns. IRR is the discount rate that sets the net present value of a fund's cash flows to zero, with remaining unrealized net asset value treated as a terminal distribution in pooled benchmark calculations. DPI is defined as cumulative distributions to limited partners divided by paid-in capital, capturing the realized cash-on-cash return to investors. We measure VC profitability relative to PitchBook benchmarks.[3] The specification includes investor fixed effects, α_i, and year fixed effects, λ_t, so that the coefficients β_h capture the dynamic within-investor response to changes in non-compete enforcement in the relevant state.

Figure 4 shows that VC profitability improves following non-compete tightening. Interpreted together with Table 5, the evidence suggests that reallocating Ph.D.-trained individuals from VC firms to entrepreneurship can improve VC performance. While Fact 2 shows that scientific human capital enhances investment decisions within VC firms, the evidence here indicates that the aggregate effects of scientific human capital depend on how it is allocated across occupations. These findings suggest that the marginal Ph.D.-trained individual may create greater value as a founder than as an investor. This finding highlights the importance of understanding the equilibrium allocation of scientific human capital between financing innovation and producing innovation.

Motivated by these three facts, Section 4 develops a dynamic general equilibrium model of scientific human capital allocation. The empirical evidence reveals three key patterns. First, scientific human capital allocated to VC firms is unevenly distributed. Second, VC firms with more scientific human capital are better able to identify and finance high-quality deep-tech startups. Third, reallocating scientific human capital between VC firms and entrepreneurship affects venture ecosystem performance. To understand the forces that jointly determine these outcomes, we develop a model in which Ph.D.-trained individuals choose between financing innovation as VC partners and producing innovation as startup founders. The model allows us to study how the equilibrium allocation of scientific human capital shapes investment patterns, startup formation, and the value created by the venture capital sector.

[3]Benchmarks are constructed by comparing funds within peer groups defined by characteristics such as asset class or strategy, vintage year, geography, and fund size, with performance generally reported net of fees and carried interest.

4 Structural Analysis

4.1 Model

Section 3 documents three empirical facts. First, scientific human capital allocated to VC firms is unevenly distributed. Second, VC firms with more Ph.D.-trained partners are better able to identify and finance high-quality deep-tech startups. Third, reallocating Ph.D.-trained individuals from VC firms to entrepreneurship can improve venture ecosystem performance. These findings suggest that scientific human capital plays two distinct roles in the innovation ecosystem. When allocated to venture capital firms, it helps finance innovation by screening and evaluating deep-tech startups. When allocated to entrepreneurship, it helps produce innovation through startup formation. Because the supply of scientific human capital is limited, allocating more Ph.D.-trained individuals to VC firms necessarily reduces the amount available for entrepreneurship, and vice versa.

To study this tradeoff, we develop a dynamic general equilibrium model of scientific human capital allocation. The model consists of VC firms and households. Households endowed with scientific human capital choose between becoming Ph.D.-trained VC partners, who help finance innovation, and becoming deep-tech startup founders, who produce innovation. VC firms hire Ph.D.-trained partners to identify and evaluate deep-tech startups in a frictional matching market. Hiring Ph.D.-trained partners is costly, but it increases a VC firm's ability to screen and match with deep-tech startups. Based on this framework, we study the equilibrium allocation of scientific human capital between financing innovation and producing innovation. We begin by describing the optimization problem faced by VC firms.

4.1.1 VC firms

Productivity and Revenue A VC firm's revenue depends on two factors: its investment capacity and the number of deep-tech startups it successfully finances. We model each in turn.

Investment capacity is determined by the firm's productivity and its employment of regular workers to process investment opportunities. VC firms are heterogeneous, each characterized by an exogenous productivity $z_{j,t}$ with an idiosyncratic productivity shock that follows a log-AR(1) process,

$$logz_{j,t+1} = \rho_z logz_{j,t} + \epsilon_{j,t+1} \tag{4}$$

where $\epsilon_{j,t+1} \sim N(0,\sigma_z^2)$ and $\rho_z \in (0,1)$. To process investment deals, firms also hire regu-

lar workers $l_{p,j,t}$. Together, productivity and regular labor determine the total amount of funding VC firms can deploy.

The gross revenue of VC firms depends not only on this capacity but also on the number of deep-tech startups the firm matches with and finances. Therefore, VC firms' revenue $y_{j,t}$ is jointly determined by capital demand and supply through a CES aggregator:[4]

$$y_{j,t} = z_{j,t} \left(l_{p,j,t}^{\frac{\sigma-1}{\sigma}} + m_{j,t+1}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{5}$$

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 (or at the beginning of the period $t+1$). Revenue is thus increasing in both the firm's deployable funding and the number of deep-tech startups in which it invests.

Frictional VC-Startup Investment Market Investments in deep-tech startups generate higher returns, but identifying them requires technical expertise. VC firms therefore employ scientific human capital (i.e., partners with Ph.D. degrees) to search for and screen new deep-tech ventures. Hiring these Ph.D. partners s is costly, which is captured by an increasing and convex cost function $\kappa(s) = \frac{\kappa}{2}s^2$, where the scalar $\kappa > 0$ governs the marginal cost of hiring.

The VC-startup investment market is frictional. Ph.D. partners are dispersed across separate local markets, and to obtain investment funding from VCs, startup founders b must meet with Ph.D. partners s. We assume that startup founders independently choose which local market to visit and that Ph.D. partners have finite capacity to screen startups. Meetings between Ph.D. partners and potential startup founders are therefore subject to coordination frictions in the search market: in each period, some local markets have no startup founders arriving, while others receive more than the Ph.D. partners can handle. This friction is captured by a VC-level directed-search matching function. When s efficiency units of Ph.D. partners meet with b units of startup founders, they generate new VC capital investment:

$$\mathbb{M}(b_{j,t}, s_{j,t}) = \xi \left(b_{j,t}^{\gamma_m} s_{j,t}^{1-\gamma_m} \right)^{\nu} \tag{6}$$

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

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

[5] This measure is the product of the exogenous probability that a meeting leads to a new investment

We use $\theta = b/s$ to denote the VC-specific average queue length of potential startups' founders across per Ph.D. partner. The probability of matching per Ph.D. partner, $\frac{\mathbb{M}(b,s)}{s} = \eta(\theta,s) = \xi\theta^{\gamma_m \nu} s^{\nu-1}$, 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 existing relationships end with probability δ_n each period. Therefore, the stock of startups financed by each VC, a form of customer capital, evolves according to:

$$m_{j,t+1} = (1 - \delta_n)(m_{j,t} + \mathbb{M}(b_{j,t},s_{j,t})) \tag{7}$$

We assume that VC firms can commit to an upfront cost $\varsigma_{j,t}$, which they use to screen and compete for new deep-tech startups.[7] In equilibrium, different VC firms incur different upfront costs depending on their desired level of startup investment.[8]

4.1.2 VC's Recursive Optimization Problem

A VC's per-period net profit can be written as

$$e_{j,t} = y_{j,t} - s_{j,t}\eta(\theta_{j,t},s_{j,t})\varsigma_{j,t} - w_t l_{p,j,t} - w_t \frac{\kappa}{2} s_{j,t}^2 \geq 0 \tag{8}$$

where w_t is the wage rate for working in VC firms. $\frac{\kappa}{2} s_{j,t}^2$ functions as the adjustment cost for recruiting Ph.D. partners. The original value of the VC's equity, $v(z,m)$, depends on two state variables $S = (z,m)$, which are productivity z and the stock of invested deep-tech capital m.

Every period, a VC firm chooses the number of Ph.D. partners $s_{j,t}$ to recruit, the amount of upfront costs $\varsigma_{j,t}$ it pays to identify and compete for new profitable startups, and the

relationship and the measure of meetings taking place. For simplicity, we assume constant returns to scale for the matching technology, $\nu = 1$.

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

[7] We assume that this upfront payment is received by the invested startups as a one-time bonus.

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

revenue $y_{j,t}$ it produces to maximize its recursive value function:

$$\begin{aligned} v_t(z,m) =& \max_{y,s,\varsigma} \; e + \beta \mathbb{E}_t v_{t+1}(z', m') \\ e =& y - s\eta(\theta, s)\varsigma - w_t l_p - w_t \frac{\kappa}{2} s^2 \\ y =& z \left(l_p^{\frac{\sigma-1}{\sigma}} + m'^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\ m' =& (1-\delta_n)(m + s\eta(\theta,s)) \\ \log(z') =& \rho_z \log(z) + \epsilon_z \end{aligned} \tag{9}$$

where β is the discount factor. All choice variables are nonnegative. In each period, offering a higher bonus lowers current VC profits but generates more new investment capital and higher future profits.

In every period, households make an occupational choice between becoming startup owners and Ph.D. partners. A household that becomes a startup owner receives the expected one-time bonus $\mu(\theta, s)\varsigma$ from VC firms, while one that becomes a Ph.D. partner earns salary plus a non-wage benefit, $w_t + \Delta$. In practice, Δ captures the non-wage incentive of becoming a VC partner, including factors such as lower risk, greater job mobility and security, prestige, and professional networks. In equilibrium, households are indifferent between the two roles, so their indifference condition is $\mu(\theta, s)\varsigma = w_t + \Delta$.

Proposition 2: The optimal conditions of VC imply that

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

The proof of Proposition 2 can be found in the Appendix. In equilibrium, the optimal choice of Ph.D. partners depends on the ratio of the non-wage benefit to the wage rate, Δ/w, and on the number of deep-tech startups b that they identify and finance. As Δ increases, the marginal cost of hiring Ph.D. partners relative to building an investment relationship with deep-tech startups decreases. This gives VC firms a stronger incentive to hire Ph.D. partners s and increases total VC investment value. At the same time, a higher Δ draws households away from founding, so the equilibrium number of deep-tech startups b declines. This lowers the equilibrium amount of deep-tech capital investment and reduces total investment value. Taken together, these two forces imply that total VC investment value is hump-shaped in the non-wage benefit Δ.

4.1.3 Household Sector

There is a unit-measure continuum of identical households with preferences over consumption C_t and total labor supply $L_t^b + L_t^m$, where L_t^m is market work for VC firms and L_t^b is funding search as a startup owner in the VC–startup market. 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

$$C_t + \frac{B_{t+1}^{rf}}{1 + r_t} \leq w_t L_t^m + (w_t + \Delta) L_t^b + B_t^{rf} + T_t, \tag{10}$$

where β is the discount factor, r_t the risk-free rate, w_t the wage rate, B_t^{rf} one-period risk-free bond holdings, and T_t 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:

$$w_t = -\frac{U_l(C_t, L_t^b + L_t^m)}{U_c(C_t, L_t^b + L_t^m)}. \tag{11}$$

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

4.1.4 Model Equilibrium

Given equilibrium prices w and r, a stationary competitive search equilibrium specifies the 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) households' occupational choice satisfies $\mu(\theta, s)\varsigma = w + \Delta$ with $\theta > 0$; and (3) all markets clear:

Consumption goods market clears. The sum of consumption and the non-wage benefit of Ph.D. partners should equal total revenue in the economy.

$$C_t + \Delta \int \frac{\kappa}{2} s_t^2 d\phi(S) = Y_t = \int y_t d\phi(S). \tag{12}$$

Matching consistency. In the competitive search market, the total number of startup own-

ers should equal the total number matched with Ph.D. partners.

$$L^b = \int s\theta d\phi(S). \tag{13}$$

Labor market clears. Aggregate labor demand, including regular workers, Ph.D. partners, and startup owners, should equal total household labor supply, and we exogenously set total labor supply $L^m + L^b$ in this economy to 1:

$$L^m + L^b = \int \left(\frac{\kappa}{2}s^2 + l_p + s\theta\right) d\phi(S) = 1. \tag{14}$$

4.2 Quantitative Analysis

In this section, we perform the quantitative analysis through calibration and simulation. We start with the annual calibration, followed by a discussion of the model mechanisms and policy function. To compare our model with the data, we simulate a panel of 5,000 firms for 50 years ten times and compute the cross-simulation average of the target moments.

4.2.1 Model Calibration

The calibration of the parameters is summarized in Table 6. 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 VCs depends on an exogenous productivity process that affects VC valuations and earnings. We calibrate the parameters that govern capital supply, $\rho_z = 0.88$ and $\sigma_z = 0.05$, to match the average earnings-to-capital ratio and the autocorrelation of VC earnings for all U.S. VCs with reported Ph.D. partners and at least three years of observations. We calibrate the degree of complementarity parameter σ between the supply and demand of capital to match the IRR of VCs.

The investment relationship between VC firms and deep-tech startups is sticky, and forming such a relationship requires effort from Ph.D. partners to identify high-potential deep-tech startups accurately. This process entails substantial costs, including wage expenses for Ph.D. partners and regular workers, as well as upfront costs associated with screening and competing for profitable deep-tech startups rather than non-deep-tech startups. We calibrate κ to 18 to match the average ratio of total wage expenses for Ph.D. partners to total wage expenses for all employees within each VC. 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, $\delta = 0.2$, from the average growth rate of total invested deep-tech capital. We calibrate the matching efficiency ξ to 0.05 to match the observed average ratio of new investment to existing investment. Finally, the matching elasticity γ_m is set to 0.76 to match its empirical value estimated in the data.

When making occupational choices each period, households face a non-wage benefit Δ when working as Ph.D. partners. We calibrate this non-wage benefit to match the average ratio of the number of Ph.D. partners to the number of deep-tech startups in equilibrium. The supply of talent in the economy is limited, and we exogenously set the total supply of labor to 1. The discount factor β is set to 0.97 to match a 3% annual risk-free rate.

4.2.2 Model Implications

In this section, we test two implications of the model. First, we examine whether the Ph.D. partner ratio predicts the VC investment rate, labor costs, and returns. Second, we examine whether the matching probability predicts these outcomes.

Ph.D Partners Ratio, Investment, and Return The model mechanism suggests that VCs with a higher Ph.D. partner ratio, $s/(l_p + s)$, have higher investment rates and higher VC value. We use the simulated data to estimate the following regression specification:

$$y_{i,t+1} = \alpha_i + \beta_i \frac{s_{i,t}}{s_{i,t} + l_{p,i,t}} + \epsilon_{i,t+1} \tag{15}$$

where $y_{i,t+1}$ is average labor cost, defined as the wage expense of Ph.D. partner hiring per unit of capital, $\frac{w\kappa s^2}{2m}$; the VC investment rate, defined as the ratio of new investment to total existing capital, $\frac{\mathbb{M}}{m}$; or IRR in percentage points. Panel A of Table 7 shows that the coefficient estimates on the Ph.D. partner ratio are all positive: more Ph.D. partners lead to more investment in deep-tech startups and therefore higher returns.

Heterogeneous Matching Probability In the model, the average queue length of startups per VC Ph.D. partner is represented by $\theta = b/s$. A higher value of θ indicates that deep-tech startups require relatively more funding than VCs supply. In other words, Ph.D. partners, on average, are able to identify more deep-tech startups and generate more profit. Therefore, a higher value of θ implies a higher probability that a Ph.D. partner succeeds in matching, measured by $\eta(\theta)$. A higher matching probability predicts more investment

and a higher return on VC investment. Panel B of Table 7 shows the coefficient estimates on the matching probability $\eta(\theta)$.

4.3 Counterfactual Analysis

How do changes in the equilibrium Ph.D. partner ratio affect the aggregate value of the VC sector, and what does this imply for policy? The Ph.D. partner ratio summarizes how scientific human capital is allocated between financing innovation, as VC partners, and producing it, as startup founders. From a policymaker's perspective, the question is whether, in the current economy, talent should be encouraged toward the financing side or the founding side. To address this, we use the calibrated model to conduct a counterfactual analysis, treating the non-wage benefit Δ as a policy lever that shifts the equilibrium allocation of human capital. As discussed above, a higher Δ makes VC partnership relatively more attractive and pulls human capital toward the financing side, whereas a lower Δ shifts it toward founding. By varying Δ, we trace out the resulting changes in the equilibrium Ph.D. partner ratio and aggregate VC value.

In the baseline model, aggregate labor supply is set exogenously to 1 and Δ is set to 0.03. In the counterfactual analysis, we vary Δ from -0.06 to 0.15 and solve for the steady-state equilibrium and aggregate ratios.

Figure 6 plots the non-wage-to-wage benefit for Ph.D. partners, $\frac{w+\Delta}{w}$, aggregate Ph.D. partners s, the aggregate ratio of Ph.D. partners to startup owners s/b, the equilibrium wage rate, aggregate new investment, and aggregate VC value. As the relative marginal cost of screening for profitable deep-tech startups increases, the equilibrium number of startups b decreases. From Proposition 2, equilibrium hiring of Ph.D. partners is positively related to both the equilibrium number of startup owners b and the non-wage-to-wage benefit, $\frac{w+\Delta}{w}$. As Δ increases, the relative marginal cost of hiring Ph.D. partners decreases, which encourages more hiring and higher value in equilibrium. At the same time, the equilibrium number of startup owners decreases because talent supply is limited, reducing demand for Ph.D. partners and lowering matched investment in equilibrium. In the current model setup, the former force dominates the latter in Ph.D. partner hiring, generating an increase in the equilibrium number of Ph.D. partners. These two competing forces, together with a hump-shaped equilibrium wage rate, generate hump-shaped aggregate new investment in deep-tech capital and hence hump-shaped aggregate VC value.

The hump-shaped relationship between aggregate VC value and Δ helps explain why the number of Ph.D.-trained partners can be low in VC firms. The calibrated value of Δ in the baseline model is 0.03, which lies on the right side of the aggregate value curve. From

that point, a further increase in Δ raises the equilibrium number of Ph.D. partners only moderately, while sharply increasing the screening cost of profitable deep-tech startups and reducing the equilibrium number of matched startups. Aggregate VC value therefore declines, weakening VC firms' incentives to recruit additional Ph.D.-trained partners and sustaining a low allocation of scientific human capital to VC firms.

4.3.1 Analogous Exercise of Non-compete Agreement

The empirical analysis in the previous section shows that non-compete tightening reduces the endogenous supply of Ph.D. partners by raising the probability that Ph.D. partners switch into startup ownership. A higher NCEI represents stricter enforcement of non-compete agreements, which implies lower labor mobility and, therefore, a lower value of outside options that motivate Ph.D. partners. In other words, non-compete tightening can be interpreted as a negative exogenous shock to the non-wage benefit Δ of working as a Ph.D. partner.

To construct the model counterpart, we first solve two steady-state equilibria, one with a high non-wage benefit Δ and one with a low non-wage benefit. We then simulate a panel for 300 periods. For the first 200 periods, we simulate 10,000 firms with a high value, $\Delta = 0.06$. In period 201, we reduce Δ to 0.035 (the baseline value), which mimics an increase in NCEI, and continue to simulate the panel for another 100 periods using the low-Δ steady-state policy functions. We plot the aggregate ratio of Ph.D. partners to startups and the aggregate value of the VC sector before and after the negative shock to Δ. We set the period to zero when the shock takes place. The results are plotted in Figure 5. The model predicts that the equilibrium ratio of Ph.D. partners to startups drops while aggregate VC-sector value increases after a reduction in the non-wage benefit Δ. This is consistent with what we observe in the data: a reduction in the value of outside options due to stricter non-compete enforcement endogenously reduces the equilibrium number of Ph.D. partners.

4.3.2 Geographical Heterogeneity

Finally, we use the calibrated model to understand market structure and aggregate VC value in different local markets. Specifically, we study the VC markets in California, Massachusetts, New York, and Texas by calibrating the parameter Δ to match the ratio of Ph.D. partners to the total number of deep-tech startups and Ph.D. partners in these four local markets. Table 8 shows the calibrated values for Δ, and Figure 6 highlights the equilibrium values for the four states. Comparing aggregate VC-sector values across these local

markets suggests that Texas and New York are close to the optimal labor-market structure indicated by the Ph.D. partner ratio. Changes in the non-wage benefit of working as a Ph.D. partner would lower aggregate deep-tech capital investment and VC value. In other words, VCs have no incentive to increase Ph.D. partner hiring because it would reduce profitability. The labor market structures of California and Massachusetts are far from optimal, with an oversupply of Ph.D. partners relative to startup owners: 46% and 69% higher, respectively, than the equilibrium Ph.D. ratios in New York. This leads to aggregate VC-sector values that are 1.4% and 3.5% lower, respectively, than in New York.

Taken together, the counterfactual results show that raising the equilibrium Ph.D. partner ratio does not necessarily increase the aggregate value of the VC sector. Because the baseline economy lies on the downward-sloping side of the hump-shaped value curve, the marginal unit of scientific human capital creates more value on the founding side than on the financing side: shifting talent away from VC partnership—for example, through a tightening of non-compete enforcement that lowers Δ—raises aggregate VC value even as it lowers the equilibrium Ph.D. partner ratio. This mechanism helps rationalize the persistently low and declining presence of Ph.D. partners in the industry. The geographic analysis reinforces this conclusion and adds a spatial dimension: Texas and New York sit close to the value-maximizing allocation, whereas California and Massachusetts hold an oversupply of Ph.D. partners relative to founders and would gain from reallocating talent toward founding. The optimal allocation of scientific human capital thus varies across local markets, suggesting that place-based policies are likely to be more effective than uniform national interventions.

5 Conclusion

This paper studies how the allocation of scientific human capital shapes VC industry profitability. We document three empirical facts. First, scientific human capital allocated to VC firms has declined over time despite growing demand for financing among deep-tech startups. Second, VC firms with a higher share of Ph.D.-trained partners are more likely to invest in deep-tech startups, and the startups they select exhibit better performance. Third, reallocating Ph.D.-trained individuals from VC firms to entrepreneurship improves VC performance.

These findings highlight two distinct roles of scientific human capital in the innovation ecosystem. When allocated to venture capital firms, scientific human capital helps finance innovation by improving the screening and evaluation of deep-tech startups. At the same time, scientific human capital is also a critical input into producing innovation through

entrepreneurial activity. The value created by scientific human capital, therefore, depends not only on its productivity within a given occupation but also on how it is allocated across occupations.

To understand this tradeoff, we develop a dynamic general equilibrium model in which households choose between becoming Ph.D.-trained VC partners and deep-tech startup founders. VC firms hire Ph.D.-trained partners to identify and finance deep-tech startups in a frictional matching market, while entrepreneurs create the pool of ventures seeking financing. The model highlights a fundamental tension: allocating more scientific human capital to VC firms improves the ability of VC firms to identify and finance deep-tech startups, but reduces the amount of scientific human capital available for entrepreneurship.

The quantitative analysis reveals that aggregate VC value is hump-shaped in the allocation of scientific human capital. Increasing the share of Ph.D.-trained VC partners initially improves investment outcomes by expanding screening capacity and increasing deep-tech investment. However, beyond a certain point, further reallocating scientific human capital toward VC firms reduces startup formation and lowers the supply of investment opportunities. As a result, increasing the equilibrium share of Ph.D.-trained partners does not necessarily increase the aggregate value of the VC sector.

More broadly, our findings suggest that understanding innovation requires studying both the financing and production sides of the innovation process. Policies aimed at increasing scientific talent in venture capital may improve investment decisions within firms, but can also affect the supply of entrepreneurial talent. The optimal allocation of scientific human capital therefore depends on the balance between financing innovation and producing innovation, as well as the local conditions that shape this tradeoff.

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Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Q25	Median	Q75	Max
Ph.D. Ratio	208,684	0.08	0.17	0.00	0.00	0.00	0.08	1.00
Deep Tech Indicator	208,684	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Year Founded	208,684	2015	4.84	2000	2012	2016	2019	2023
Founder Ph.D. Count	208,684	0.29	0.72	0.00	0.00	0.00	0.00	9.00
Closed	208,684	3.42	18.20	0.00	0.00	0.00	0.00	100.00
M&A	208,684	14.10	34.80	0.00	0.00	0.00	0.00	100.00
IPO	208,684	5.07	21.90	0.00	0.00	0.00	0.00	100.00

Notes: This table reports summary statistics for key variables at the VC-startup-deal level. *isDeepTech* is a binary variable indicating whether a firm has posted at least one job listing requiring a Ph.D. degree. Closed 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 equal to 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: Investor Characteristics by State

State	Deep-Tech	Ph.D. Count	Deal Count	Ph.D./Deal Intensity	Ph.D. Share
California	0.46	0.64	5.56	0.17	0.13
New York	0.44	0.36	4.50	0.11	0.07
Massachusetts	0.43	1.24	4.15	0.19	0.15
Texas	0.37	0.28	3.51	0.13	0.08
Florida	0.35	0.23	2.52	0.11	0.07
Illinois	0.40	0.41	3.57	0.11	0.07
Washington	0.36	0.26	3.64	0.10	0.07
Colorado	0.34	0.11	3.01	0.06	0.03
Pennsylvania	0.28	0.36	2.69	0.18	0.13
Virginia	0.36	0.25	2.88	0.07	0.07

Notes: The sample is restricted to U.S.-headquartered investors from 2000 to 2023 with non-missing average Ph.D. partner counts, at least one year with a new deep-tech investment, and at least three observed years. State-level values are computed using the VC headquarters state and are reported as averages across the filtered VC-year observations within each state. Rows are sorted in descending order by the number of VC firms in the state. Deep-Tech is the investor-level mean of an indicator equal to one if the investor makes a new deep-tech investment in a given year. Ph.D. Count is the average number of Ph.D. partners across observed years. Deal Count is the investor-level mean number of deals across observed years. Ph.D.-to-Deal Intensity is defined as the Ph.D. partner count divided by the sum of the number of deals and the Ph.D. partner count, and is set to missing when both terms are zero. Ph.D. Share is defined as the Ph.D. partner count divided by the total number of partners.

Table 3: Investment Decision: OLS and IV Estimates

	OLS		**IV**	
	(1)	(2)	(3)	(4)
Ph.D. Ratio × Deep Tech	0.779***	0.707***	3.794***	2.281**
	(0.159)	(0.154)	(1.159)	(1.094)
Ph.D. Ratio	-0.089		-2.921***	
	(0.085)		(0.939)	
Company × Year FE	Y	Y	Y	Y
VC × State × Year FE		Y		Y
Observations	10,862,927	10,862,927	7,905,264	7,905,264
R^2	0.284	0.304	0.301	0.319
F-statistic	–	–	40.1	64.6

Notes: This table reports OLS and second-stage IV results for the effect of Ph.D.-holding partners on investment choice. The dependent variable is an indicator (0 or 100). In the IV specifications, *PhDRatio* is instrumented by the lagged peer Ph.D. ratio (Z_{t-1}). Columns (1) and (3) include company-year fixed effects. Columns (2) and (4) include VC-state-year fixed effects. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 4: Investment Performance: OLS and IV Estimates

	OLS		**IV**	
	Close	**M&A and IPO**	**Close**	**M&A and IPO**
	(1)	(2)	(3)	(4)
Deep Tech × Ph.D. Ratio	-4.239***	9.344***	-11.862***	32.799***
	(1.080)	(1.774)	(3.075)	(6.080)
Deep Tech	-1.478***	-2.182***	-0.873***	-4.112***
	(0.147)	(0.330)	(0.251)	(0.560)
Controls	Y	Y	Y	Y
VC × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
Observations	208,684	208,684	194,290	194,290
R^2	0.246	0.415	0.228	0.401
F-statistic	–	–	104.1	104.1

Notes: This table combines OLS and second-stage IV results for investment performance. The dependent variable in Columns (1) and (3) is an indicator (0 or 100) for company failure (Close). In Columns (2) and (4), the dependent variable is an indicator for successful exit (M&A or IPO). In the IV specifications, *PhDRatio* is instrumented by the lagged peer Ph.D. ratio. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Non-compete tightening reduces Ph.D. partner supply

	% Ph.D. Partner → Founder		Ph.D. Partner / Ph.D. Founder	
	(1)	(2)	(3)	(4)
NCEI	0.527***	0.340*	-1.626	-2.339**
	(0.139)	(0.193)	(1.036)	(1.153)
State FE	Y	Y	Y	Y
Year FE		Y		Y
Observations	826	826	646	646
R^2	0.073	0.101	0.221	0.258

Notes: Unit of observation is state-year. Columns (1)–(2) use the job-switch panel; the dependent variable is the percentage of Ph.D.-holding VC partners who transition to founder, computed as Ph.D. partner-to-founder switches divided by lagged Ph.D.-holding VC partners and multiplied by 100. Columns (3)–(4) use the balanced state-year panel; the dependent variable is total Ph.D. partner count divided by total Ph.D. founder count, with state-years with zero Ph.D. founders coded missing. NCEI is the state-year non-compete enforceability index. Standard errors clustered by state are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Model Calibration

Parameter	Value	Moments	Data	Model
ρ_z	0.88	Earnings correlation	0.82	0.77
σ_z	0.05	Earnings/capital	0.27	0.23
δ	0.2	Inferred depreciation rate	0.21	0.20
γ_m	0.76	Matching elasticity	0.76	0.76
ξ	0.05	$\frac{\text{Average new investment}}{\text{Existing capital}}$	0.28	0.25
κ	18	$\frac{\text{Wage expense on Ph.D. partners}}{\text{Total wage expense}}$	0.54	0.56
σ	0.05	IRR (%)	4.5%	2.71%
Δ	0.03	$\frac{\text{\# of Ph.D.}}{\text{\# of Startups}}$	0.167	0.168
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 7: Model Implications

	Average Labor Cost	New Investment Rate	IRR
		Panel A	
Ph.D. partner ratio $\frac{s}{l_p + s}$	2.80	4.06	1.83
		Panel B	
Matching probability $\eta(\theta)$	1.78	1.35	0.61

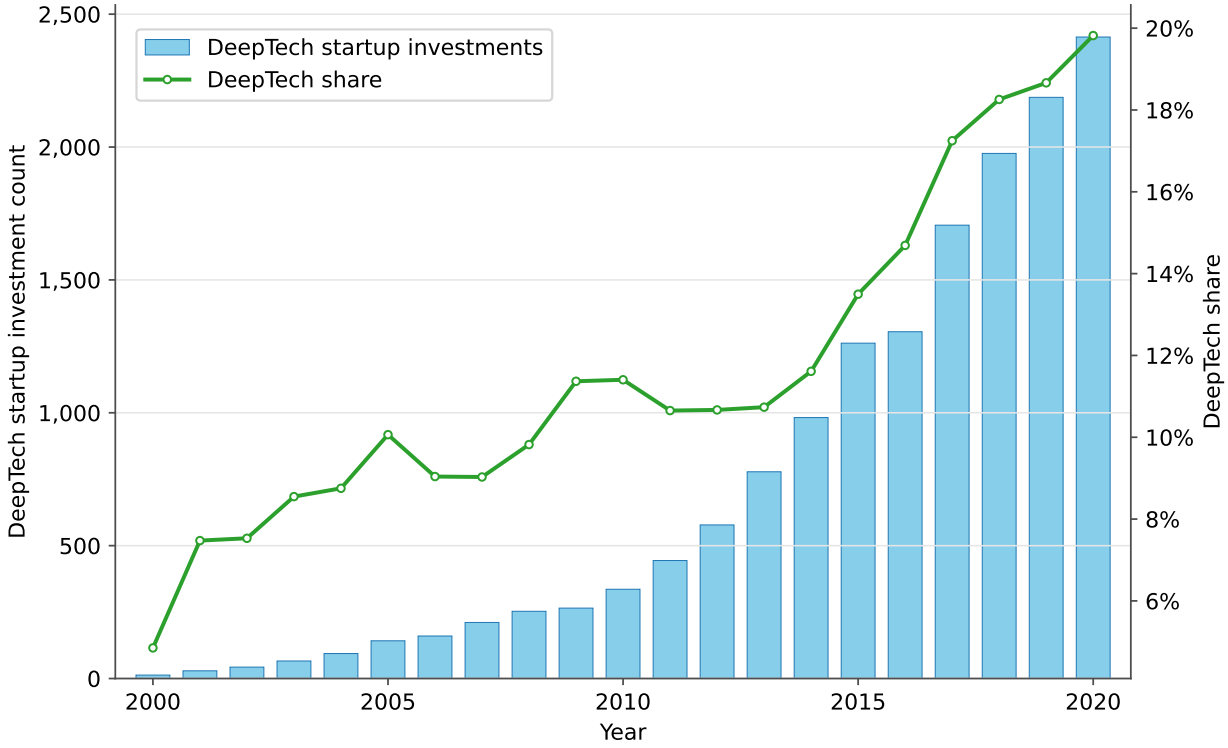
Notes: This table presents model implications using simulated data from the calibrated model. Panel A estimates the predictability of the Ph.D. partner ratio, defined as the ratio of Ph.D. partners to total employees, for VC investment rates, new matched investment relationships, and IRR. Panel B estimates the predictability of the matching probability $\eta(\theta) = \xi\theta^{\gamma}$, which is an increasing function of the ratio of startups to Ph.D. partners, for VC investment and returns.

Table 8: Model Counterfactual

State	California	Massachusetts	New York	Texas
$\frac{\text{Ph.D. Partners}}{\text{Startups + Ph.D. Partners}}$	0.19	0.22	0.13	0.15
Δ	0.07	0.12	-0.02	0

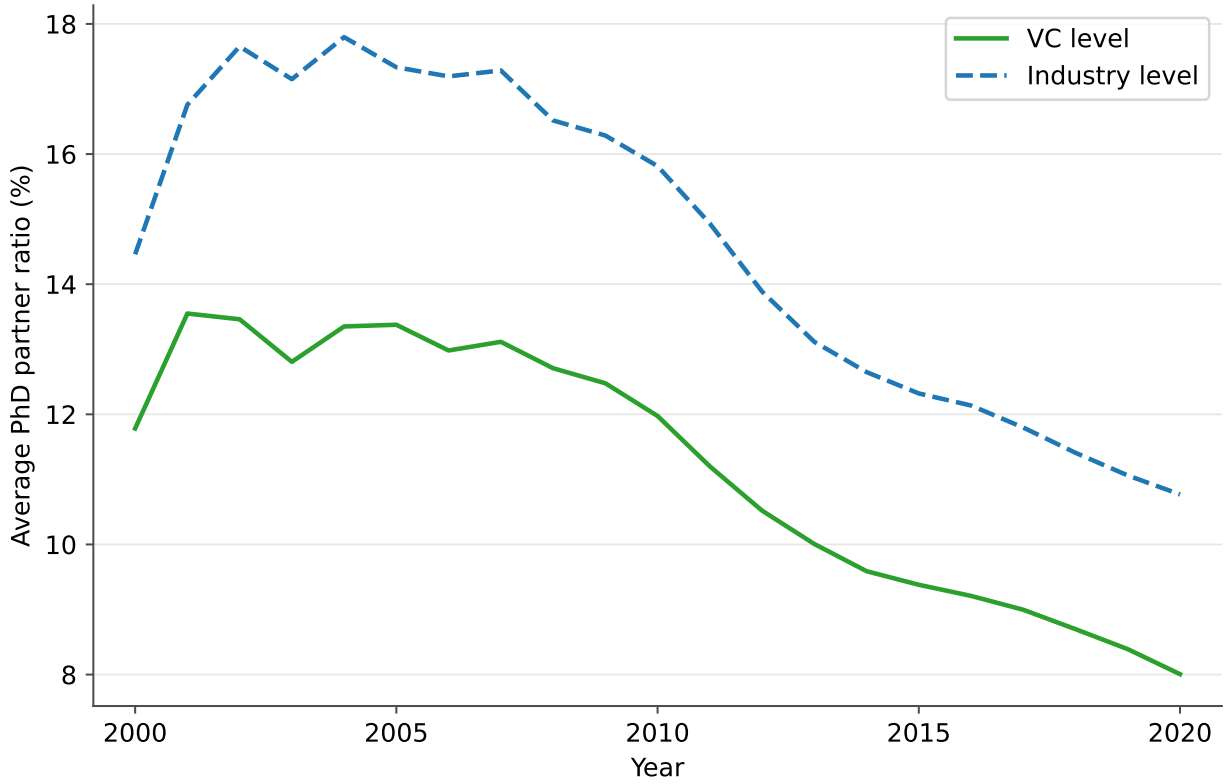
Notes: This table presents the counterfactual analysis of the calibrated model. The first row shows the ratio of Ph.D. partners to startups in the data for four states with relatively more deep-tech startups: California, Massachusetts, New York, and Texas. The second row shows the calibrated values of Δ that match the Ph.D. partner ratio in the model for the four states.

Figure 1: Investment into Deep Tech Startups



Notes: This figure plots deep-tech startup investments over time. The bars represent the annual number of deep-tech startup investments, calculated as the total count of deep-tech startup investments in each year. The line represents the weighted share of deep-tech startups among all startup investments, computed as the number of deep-tech startup investments divided by the total number of startup investments in each year. The data are sourced from PitchBook, and the sample corresponds to the dataset used in our regression analysis, which includes investments involving U.S. startups founded between 2000 and 2023.

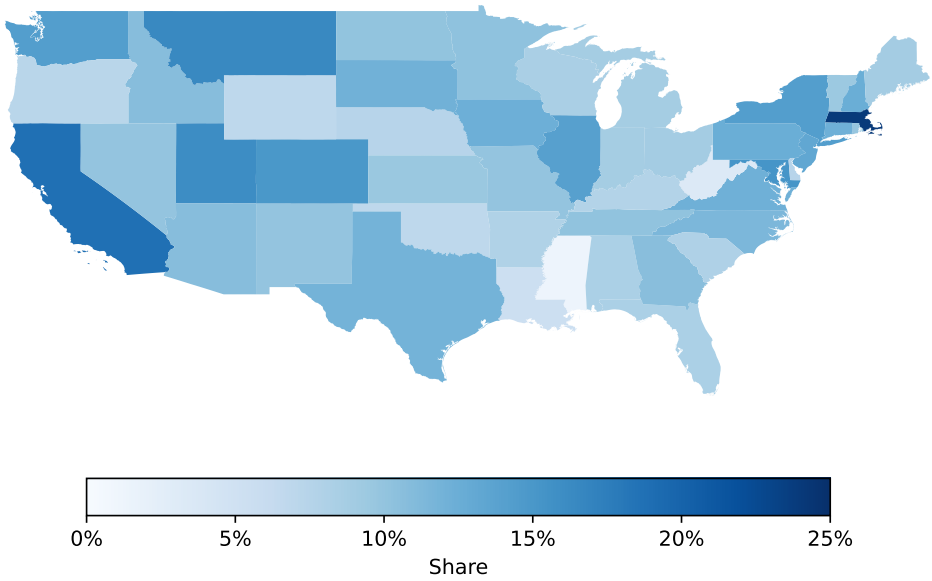
Figure 2: Ph.D. in the VC Industry



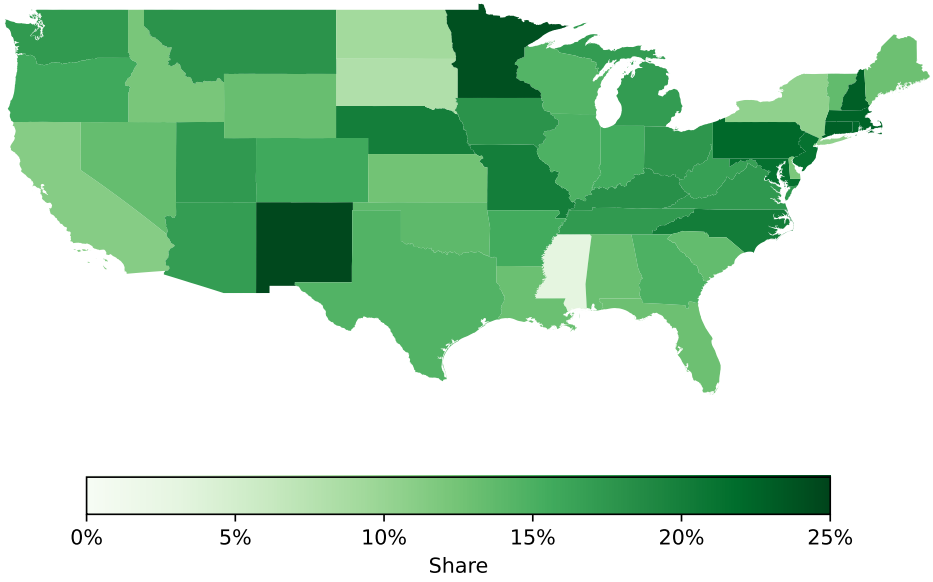
Notes: This figure plots the ratio of Ph.D. partners in the VC industry. The green line represents the overall share of Ph.D. partners among all VC partners in the industry. It is calculated as the total number of Ph.D. partners divided by the total number of partners in the VC industry for each year. The blue line measures the average ratio of Ph.D. partners at the firm level, computed as the mean Ph.D. ratio across VC firms in each year. The data are 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 2020.

Figure 3: Geographic Allocation of Scientific Human Capital

(a) Share of Deep-Tech Startups

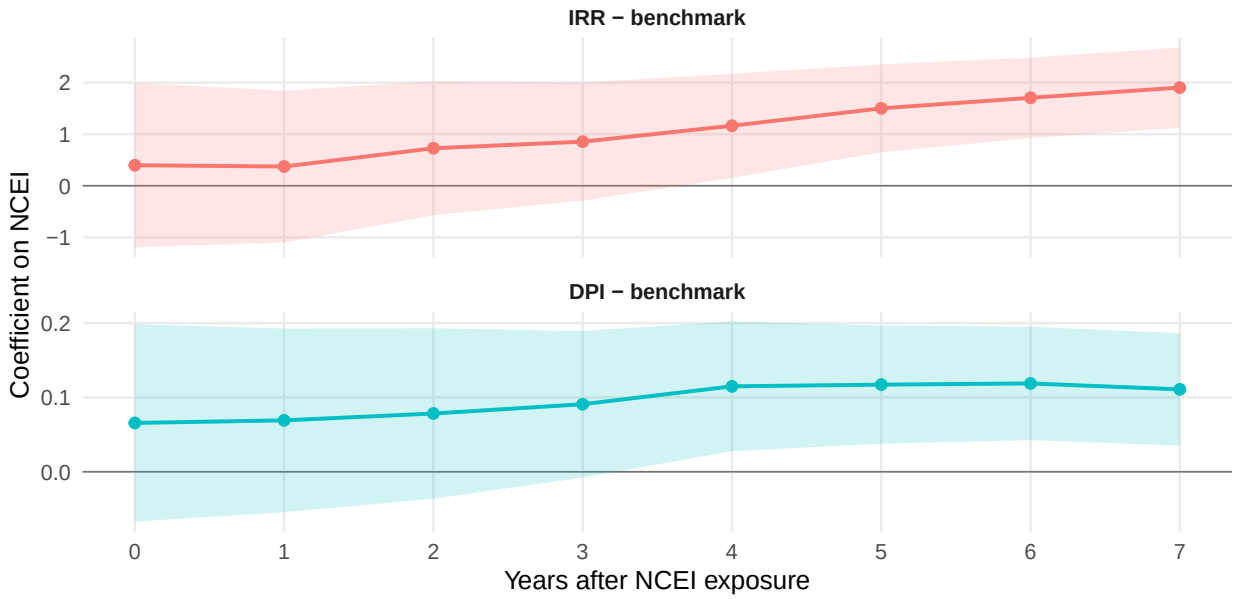


(b) Share of VCs with Ph.D. Partner(s)



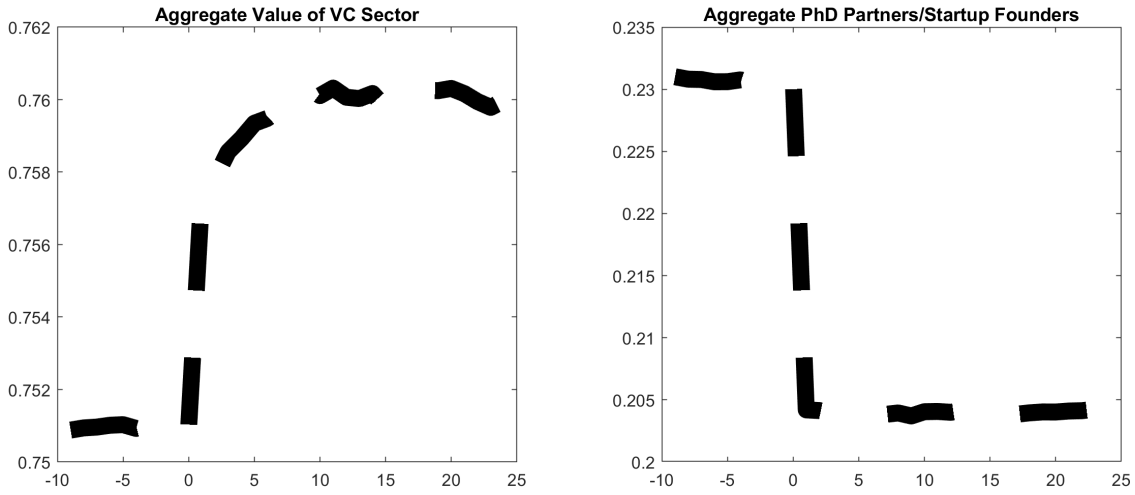
Notes: This figure reports the ratio of deep-tech startups along with the ratio of VCs with Ph.D. partners by state. Weighted averages are used when aggregating data from the state-year level to the state level, with weights given by the relevant state-year denominator. Figure (a) plots the share of 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 Ph.D. 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 by U.S. investors involving U.S. startups founded between 2000 and 2023.

Figure 4: Non-compete tightening improves VC profitability



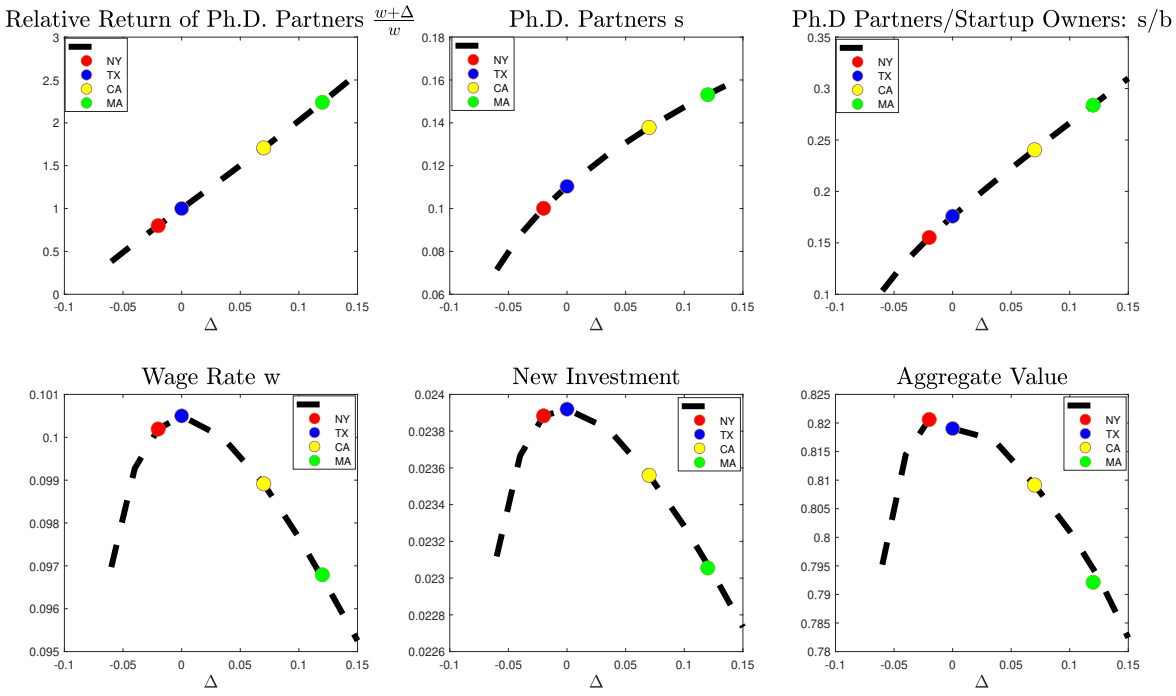
Notes: This figure reports local-projection estimates of VC return outcomes on state-year non-compete enforceability. For each horizon $h = 0, \ldots, 7$, the outcome for investor i in year $t + h$ is regressed on NCEI in investor state-year t, with investor and year fixed effects. Outcomes are IRR minus benchmark and DPI minus benchmark. The sample is U.S.-based VC investors appearing in the regression data sample matched to state-year NCEI. Shaded bands show 90 percent confidence intervals based on standard errors clustered by investor.

Figure 5: Negative Shock to Non-wage Benefit Δ



Notes: This figure plots the equilibrium ratio of Ph.D. partners to startups and aggregate VC-sector value following a negative shock to the non-wage benefit at time 0 that reduces Δ from 0.1 to 0.035.

Figure 6: Counterfactual Analysis: Aggregate Labor, Investment, and Value



Notes: This figure plots the aggregate VC wage rate, aggregate labor, aggregate new investment, and aggregate value from model equilibrium when we exogenously vary Δ from -0.06 to 0.15. Heterogeneity for four states—California, Massachusetts, New York, and Texas—is also highlighted in this figure.

Internet Appendix for

"Financing or Producing Innovation? The Allocation of Scientific Human Capital"

Yuchen Chen, Can Huang, Xuelai Li

June 2026

A Scientific Human Capital in VC firms

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.[9] 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 toward 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 under 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. By contrast, 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 uncertainty 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

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

investors had deep technical expertise, today's VC professionals are more likely to come from backgrounds in business administration (i.e., MBA) or finance. Consequently, VC firms with fewer Ph.D.-trained partners 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 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 declining allocation of scientific human capital to VC firms 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 startups' technological potential, scalability, and risks. Without the necessary expertise, such misjudgment can lead investors to favor more familiar business models with clearer pathways to profitability.

Beyond the initial investment decision, VC firms with Ph.D.-trained partners can play a crucial role in the long-term success of deep-tech startups. Their understanding of technology 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 startups after investment.

B Algorithm

Guess the initial wage rate w.

1. Given the state variables (z,m), choose 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 the 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: $E_z V_{t+1}^{new}(z, m') = E_z V_t^0(z_{-1}, m)$.

5. Iterate the procedure until the error of the expected value function is sufficiently small.

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.

C Optimal Conditions

This section derives the optimal conditions:

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

For choice variables (l_p,s,ς,θ), the optimal conditions are:
$[l_p]$

$$l_p = m' \left[(w/z)^{\sigma-1} - 1 \right]^{\frac{\sigma}{1-\sigma}} \tag{16}$$

$[s]$

$$w \frac{\kappa'(s)}{\eta(\theta)} + \varsigma = V_m \tag{17}$$

$[\varsigma]$

$$\varsigma = \gamma_m V_m \tag{18}$$

The above two equations together give:

$$w \frac{\kappa'(s)}{\eta(\theta)} = \left(\frac{1}{\gamma_m} - 1 \right) \varsigma \tag{19}$$

The household's indifference condition for occupational choice is

$$\mu(\theta)\varsigma = w + \Delta \tag{20}$$

which is

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

Equations (19) and (20) imply

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

Appendix Tables

Table A1: 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 Ph.D. Count	0.228	0.550	0.239	0.609	0.011
Founder Ph.D. 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 A2: Distribution of Major Fields and Ph.D. Ratios

Major Field	Count	Ph.D. 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 Ph.D. ratios. The data are 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 that participated in at least one VC funding round for a U.S. startup founded between 2000 and 2023.

Table A3: 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 Ph.D. levels. The data reflect the educational backgrounds of VC partners, highlighting the prevalence of degrees in economics, finance, and business. The data are from PitchBook. The sample of VC firms is consistent with our regression analysis dataset, which includes all VC firms that participated in at least one VC funding round for a U.S. startup founded between 2000 and 2023.

Table A4: Scientific Human Capital by Deep-Tech Deal Status

	Deep Tech	Non-Deep Tech
Ph.D. Ratio (%)	10.83	7.37
STEM Ph.D. Partner Ratio (%)	8.82	5.46
STEM Ph.D./M.Sc. Partner Ratio (%)	19.39	15.46
STEM Ph.D./M.Sc. Employee Ratio (%)	17.48	14.01

Notes: This table reports the average investor human-capital of Deep Tech and Non-Deep Tech startups at deal level. *Ph.D. Ratio* is the share of partners with Ph.D. degrees. *STEM Ph.D. Partner Ratio* is the share of partners with STEM Ph.D. degrees. *STEM Ph.D./M.Sc. Partner Ratio* is the share of partners with at least a STEM master's or Ph.D. degree. *STEM Ph.D./M.Sc. Employee Ratio* is the share of all employees with at least a STEM master's or Ph.D. degree.

Table A5: Robustness Checks – Lead Partner Education and Investment Decision

	DeepTech		
	(1)	(2)	(3)
Lead Ph.D. Partner	0.083***		
	(0.017)		
Lead STEM Ph.D. Partner		0.086***	
		(0.018)	
Lead STEM Partner			0.035***
			(0.010)
Investor × Year FE	Y	Y	Y
Observations	75,796	75,796	75,796
R^2	0.374	0.374	0.373

Notes: This table reports the relationship between lead partner education and investment in deep-tech startups. The dependent variable is an indicator for whether the deal involves a deep-tech startup. Column (1) uses an indicator for whether the lead partner has a Ph.D. Column (2) uses an indicator for whether the lead partner has a STEM Ph.D. Column (3) uses an indicator for whether the lead partner has a STEM background. All specifications include investor-year fixed effects. Standard errors are clustered by investor and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Robustness Checks – STEM Degrees and Investment Decision

	Investment		
	(1)	(2)	(3)
STEM Ph.D. Partner Ratio × Deep Tech	1.211***		
	(0.202)		
STEM Ph.D./M.Sc. Partner Ratio × Deep Tech		0.524***	
		(0.090)	
STEM Ph.D./M.Sc. Employee Ratio × Deep Tech			0.561***
			(0.097)
Company × Year FE	Y	Y	Y
Investor × Year × HQ State FE	Y	Y	Y
Observations	10,862,927	10,862,927	11,215,938
R^2	0.304	0.304	0.304

Notes: This table reports robustness checks for the effect of STEM-trained investors on investment choice. The dependent variable is an indicator for investment in a deep-tech company, scaled from 0 to 100. Column (1) uses the share of partners with STEM Ph.D. degrees. Column (2) uses the share of partners with at least a STEM master's or Ph.D. degree. Column (3) uses the share of all employees with at least a STEM master's or Ph.D. degree. All specifications include company-year fixed effects and investor-year-HQ-state fixed effects. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Robustness Checks – STEM Degrees and Investment Performance

	Close	M&A/IPO	Close	M&A/IPO	Close	M&A/IPO
	(1)	(2)	(3)	(4)	(5)	(6)
Deep Tech × STEM Ph.D. Partner Ratio	-4.817***	11.169***				
	(1.292)	(2.058)				
Deep Tech × STEM Ph.D./M.Sc. Partner Ratio			-2.648***	4.923***		
			(0.714)	(1.461)		
Deep Tech × STEM Ph.D./M.Sc. Employee Ratio					-3.222***	6.474***
					(0.814)	(1.505)
Deep Tech	-1.524***	-2.268***	-1.384***	-2.388***	-1.323***	-2.460***
	(0.148)	(0.328)	(0.167)	(0.358)	(0.166)	(0.344)
Controls	Y	Y	Y	Y	Y	Y
VC × Year FE	Y	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y	Y
Observations	208,684	208,684	208,684	208,684	215,997	215,997
R^2	0.246	0.415	0.245	0.415	0.252	0.419

Notes: This table reports robustness checks for investment performance. The dependent variable in Columns (1), (3), and (5) is an indicator for company failure, scaled from 0 to 100. The dependent variable in Columns (2), (4), and (6) is an indicator for successful exit through M&A or IPO, scaled from 0 to 100. The table compares three measures of STEM-trained investors: the share of partners with STEM Ph.D. degrees, the share of partners with at least a STEM master's or Ph.D. degree, and the share of all employees with at least a STEM master's or Ph.D. degree. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Investment Decision: Excluding Most Frequently Invested Industries

	OLS		**IV**	
	Excl. Top 1	Excl. Top 2	Excl. Top 1	Excl. Top 2
	(1)	(2)	(3)	(4)
Ph.D. Ratio × Deep Tech	1.048***	1.249***	2.645**	2.444
	(0.292)	(0.394)	(1.244)	(1.674)
Company × Year FE	Y	Y	Y	Y
VC × State × Year FE	Y	Y	Y	Y
Observations	3,441,720	1,845,899	2,717,990	1,542,196
F-statistic	–	–	59.8	37.1
R^2	0.377	0.406	0.391	0.418

Notes: This table reports OLS and second-stage IV estimates for the effect of Ph.D.-holding partners on investment choice, excluding investments in the most frequently invested industries based on annual deal counts. Columns (1) and (3) exclude investments in the top one industry by deal count within year. Columns (2) and (4) exclude investments in the top two industries by deal count within year. The dependent variable is an investment indicator. In the IV specifications, the interaction between the Ph.D. ratio and deep-tech indicator is instrumented using the lagged peer Ph.D. ratio interacted with the deep-tech indicator. All specifications include company-year fixed effects and VC-state-year fixed effects. Standard errors, clustered at the VC level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Investment Performance: Excluding Most Frequently Invested Industries

	OLS		IV	
	Close	**M&A and IPO**	**Close**	**M&A and IPO**
	(1)	(2)	(3)	(4)
Panel A: Excluding Top 1 Industry				
Ph.D. Ratio × Deep Tech	-5.481***	8.040***	-12.459***	30.730***
	(1.407)	(2.203)	(4.177)	(9.044)
Deep Tech	-2.040***	-2.623***	-1.492***	-4.400***
	(0.200)	(0.400)	(0.338)	(0.746)
Observations	137,055	137,055	129,550	129,550
F-statistic	–	–	78.0	78.0
R^2	0.267	0.444	0.254	0.435
Panel B: Excluding Top 2 Industries				
Ph.D. Ratio × Deep Tech	-4.465***	5.690**	-10.415**	24.107**
	(1.645)	(2.648)	(5.010)	(11.295)
Deep Tech	-2.334***	-2.738***	-1.905***	-4.176***
	(0.241)	(0.462)	(0.406)	(0.889)
Observations	101,752	101,752	97,343	97,343
F-statistic	–	–	58.7	58.7
R^2	0.270	0.442	0.260	0.436
Controls	Y	Y	Y	Y
VC × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y

Notes: This table reports OLS and second-stage IV estimates for investment performance, excluding investments in the most frequently invested industries based on annual deal counts. Panel A excludes investments in the top one industry by deal count within year. Panel B excludes investments in the top two industries by deal count within year. The dependent variable in Columns (1) and (3) is an indicator for company failure (Close). The dependent variable in Columns (2) and (4) is an indicator for successful exit through M&A or IPO. In the IV specifications, the interaction between the Ph.D. ratio and deep-tech indicator is instrumented using the lagged peer Ph.D. ratio interacted with the deep-tech indicator. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Investment Decision by VC Size: OLS and IV Estimates

	OLS		**IV**	
	(1)	(2)	(3)	(4)
Panel A: Large VC				
Ph.D. Ratio × Deep Tech	2.403***	2.178***	5.740**	5.086**
	(0.743)	(0.746)	(2.434)	(2.391)
Ph.D. Ratio	-0.498		-2.313**	
	(0.357)		(1.099)	
Observations	656,052	656,052	647,002	647,002
R^2	0.418	0.425	0.418	0.425
F-statistic	–	–	4.9	16.0
Panel B: Small VC				
Ph.D. Ratio × Deep Tech	0.580***	0.542***	3.171***	1.786*
	(0.133)	(0.132)	(1.066)	(1.017)
Ph.D. Ratio	-0.080		-2.980***	
	(0.088)		(1.058)	
Observations	10,206,875	10,206,875	7,258,262	7,258,262
R^2	0.290	0.310	0.309	0.328
F-statistic	–	–	35.6	52.1
Company × Year FE	Y	Y	Y	Y
VC × State × Year FE		Y		Y

Notes: This table reports OLS and second-stage IV results for the effect of Ph.D.-holding partners on investment choice, split by VC size. Panel A uses data for Large VCs, while Panel B uses data for Small VCs. The dependent variable is an indicator (0 or 100). In the IV specifications, *PhDRatio* is instrumented by the lagged peer Ph.D. ratio. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A11: Investment Performance by VC Size: OLS and IV Estimates

	OLS		**IV**	
	Close	**M&A and IPO**	**Close**	**M&A and IPO**
	(1)	(2)	(3)	(4)
Panel A: Large VC				
Ph.D. Ratio × Deep Tech	-13.234**	21.646***	-25.034**	66.240***
	(5.573)	(6.615)	(9.641)	(16.000)
Deep Tech	-1.865***	-2.248*	-0.694	-6.678***
	(0.518)	(1.274)	(0.866)	(1.783)
Founder Ph.D. Count	-0.271	-2.509***	-0.260	-2.589***
	(0.212)	(0.605)	(0.211)	(0.602)
Observations	23,459	23,459	23,207	23,207
R^2	0.196	0.403	0.192	0.397
F-statistic	–	–	39.4	39.4
Panel B: Small VC				
Ph.D. Ratio × Deep Tech	-2.889***	7.862***	-8.156***	24.680***
	(0.906)	(1.762)	(2.833)	(6.082)
Deep Tech	-1.355***	-2.452***	-0.943***	-3.764***
	(0.157)	(0.329)	(0.249)	(0.555)
Founder Ph.D. Count	-0.467***	-0.209	-0.431***	-0.241
	(0.086)	(0.206)	(0.087)	(0.213)
Observations	185,225	185,225	171,083	171,083
R^2	0.260	0.414	0.242	0.398
F-statistic	–	–	76.1	76.1
Controls	Y	Y	Y	Y
VC × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y

Notes: This table reports OLS and second-stage IV results for investment performance, split by VC size. "Close" indicates startup failure; "M&A and IPO" indicates successful exit. In IV specifications, *PhDRatio* is instrumented by the lagged peer Ph.D. ratio. F-statistics are the Kleibergen–Paap rank LM statistic. Standard errors are clustered at the VC level. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.