Elite AI Talent and Firm Strategy:

Evidence from Academic Lineages and Firm Performance

Sagar Baviskar
Carnegie Mellon University

Lee Branstetter
Carnegie Mellon University and NBER

Liujie Wu
Carnegie Mellon University

Cameron Drayton
Carnegie Mellon University

Prasana Tambe
Wharton School of Management
University of Pennsylvania and NBER

Eduard Hovy
Language Technologies Institute, CMU
and the University of Melbourne

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Abstract

Discovering, cultivating, and deploying individuals with exceptional potential is central to innovation and growth, especially at moments of rapid technological advance. This paper examines how knowledge of new science generated by elite AI scientists ("immortals") shapes firm productivity and strategy through the movement of their graduate students ("academic children") into industry. We construct a novel dataset linking the career trajectories of approximately 22,000 graduate students of elite AI scientists across ten subdomains of AI (e.g., machine learning, natural language processing, robotics, computer vision) to the firm-level outcomes of their employers as measured in Compustat data between 1990 and 2024. Our analysis shows that firms hiring "immortal children" experience economically large and persistent productivity gains. We analyze these effects using an AI Talent Diffusion Framework (ATDF), which identifies three mechanisms: (1) knowledge transfer, (2) capability augmentation, and (3) network spillovers. Regression estimates indicate that doubling the stock of immortal children within a firm is associated with a 6–13 percent increase in total factor productivity (TFP) across multiple specifications. These findings underscore the importance of elite talent in shaping firm outcomes. We also discuss how the data and methods used in this paper could be extended to analysis of privately held firms and emerging technologies other than AI.

1.Introduction

After decades of disappointment, artificial intelligence (AI) has entered a new era of rapidly advancing capabilities (Agarwal et al., 2022; Baily et al., 2023). In the popular media, a vigorous debate is being waged between proponents of these new technologies, who believe they will bring a new era of rapid productivity growth and widespread prosperity, and skeptics, who fear an era of mass joblessness and wage stagnation for all but a small cognitive elite (Brynjolfsson and McAfee, 2014; Baily et al., 2023; Suskind, 2020). AI is widely viewed by many experts as a *general-purpose technology (GPT)* with the potential to drive broad productivity gains and alter the foundations of competition (Brynjolfsson & McElheran, 2022; Bresnahan & Trajtenberg, 1995). Yet despite the promise of AI, evidence on firm-level outcomes remains uneven. Some firms have successfully harnessed AI to achieve sustained productivity improvements, while others struggle to translate AI investments into measurable performance gains.[1] This heterogeneity raises a central question for strategy and organizational economics: what explains the uneven distribution of value capture from investments in AI adoption and innovation?

Much of the existing literature in strategic management and innovation emphasizes firm-level capabilities as a critical determinant of technological performance. Scholars highlight the role of dynamic capabilities (Teece, 2007; Helfat & Peteraf, 2003), absorptive capacity (Cohen & Levinthal, 1990), and complementary assets (Teece, 1986) in shaping how firms deploy and benefit from emerging technologies. A longstanding parallel effort in economics has sought to conceptualize and measure the "knowledge capital" of a firm along multiple dimensions and relate it to a firm's innovation outcomes (Griliches, 1984).[2] A more recent effort in economics has sought to measure and define managerial quality and relate it to firm-level productivity outcomes (Bloom and Van Reenan, 2007). All these perspectives underscore the importance of firm-specific attributes, including organizational routines, managerial choices, and institutional contexts in enabling or constraining technological adoption. However, they do not always fully contend with or measure *who* actually builds and deploys these technologies inside firms.

In the case of AI, the origins of elite talent—the training environments, mentorship lineages, and embedded knowledge structures of individuals—may be as important as organizational factors in explaining performance outcomes. Research has shown that individual scientists and engineers can exert outsized influence on the innovation trajectories of firms and on the development of young scholars (Azoulay, Zivin, & Wang, 2010; Mollick, 2012; Waldinger, 2010; Waldinger, 2016). The ability of firms to harness the power of fundamental breakthrough technologies can depend heavily on firm access to

[1] See the contrasting perspectives in Alderucci et al. (2024), McElheran et al. (2023). And Babina et al. (2024).

[2] Since it was first articulated by Pakes and Griliches (1984), the knowledge capital model of the firm has been elaborated and extended across decades of subsequent research. This intellectual tradition has viewed firm-specific knowledge capital as a key source of firm innovation capabilities.

experts trained in the limited number of scientific labs that have developed the new technologies (Zucker, Darby, and Brewer, 1998; Cockburn and Henderson, 1998; Agarwal and Henderson, 2002). Building on these insights, we argue that the academic genealogy of AI talent represents a distinct and powerful channel of knowledge diffusion that may not yet have received sufficient attention from academic researchers. In contrast, a rapidly intensifying talent war in Silicon Valley for AI experts, some of whom possess this elite training, leading to historically unprecedented payouts suggests that well-financed practitioners believe strongly in its importance (Bobrowsky et al., 2025).

Elite Talent and Academic Genealogy as a Strategic Resource

We define academic genealogy as the lineage linking graduates to their mentors, particularly elite scientists who have shaped foundational AI subfields such as machine learning, natural language processing, computer vision, robotics, and multi-agent systems. We refer to these highly influential scholars/mentors as *immortals*. Their graduates carry forward tacit frontier knowledge, methodological sophistication, and privileged access to global research networks. When firms hire these graduates, they do not simply acquire employees with generic technical skills; they embed within their organizations access to frontier expertise and relational capital that is otherwise difficult to obtain.[3]

This mechanism is consistent with prior work on star scientists and university–industry spillovers in other industry contexts, like biotechnology. Zucker, Darby, and Brewer (1998) and Cockburn and Henderson (1998) demonstrated that hiring scientists from elite universities accelerates innovation through the transfer of tacit knowledge. Azoulay et al. (2010) showed that the presence of star scientists has measurable effects on organizational performance. As in biotechnology a generation ago, the development of new products and services is being dramatically transformed by the direct application of frontier technologies to industrial R&D. An important difference is the potential scope for AI to have these effects across a much broader range of industries and technologies than the recombinant DNA revolution studied by Zucker, Darby, and Brewer. In identifying elite scientists, we emphasize the role of mentor–student relationships, believing these represent deep and durable channels of influence. The knowledge, norms, and problem-solving heuristics transmitted through this lineage shape how graduates approach research, experimentation, and application in firms.

We fully recognize that corporate efforts to use new AI technologies to develop new goods and services (or substantially reengineer existing ones) do not depend solely on the

[3] Fry and Glennon (2025) also focus on the role of elite mentors in the AI labor market. However, they emphasize the role of co-ethnic ties between mentors and mentees in the development and placement of new graduates. We acknowledge the importance of these ties, but focus instead on identifying a large set of potential mentors and their mentees across a broad range of fields and programs, regardless of the existence or non-existence of co-ethnic ties. We believe our study is complementary to that of Fry and Glennon (2025).

mentees of elite scientists. Any enterprise pursuing these investments will require a "pyramid" of talent. Some individuals in the lower levels of the pyramid may be at least partly self-taught or have no formal training in AI beyond a few undergraduate classes. Individuals in the middle levels of the pyramid may possess graduate degrees, but have no substantive connection to elite AI academic experts. Yet, these individuals are nevertheless able to make important contributions to these corporate investments. The work of Babina et al. (2024), among others, has used inclusive measures of AI talent which capture multiple levels of this pyramid; this work has demonstrated the degree to which these measures are correlated with firm growth and AI patenting.

That being said, we believe that some firms will benefit from the presence of mentees of elite scientists at the apex of their AI talent pyramids. Given the scarcity of these experts relative to current demand, where they go in terms of post-graduate employment may exert significant influence on the nature, direction, and efficacy of AI-related R&D. Our preliminary results provide support for this hypothesis.

The AI Talent Diffusion Framework

To conceptualize how genealogy shapes firm outcomes, we develop the AI Talent Diffusion Framework (ATDF). The ATDF highlights three interrelated mechanisms through which the academic children of AI immortals may influence firm performance:

1. Knowledge transfer: graduates bring cutting-edge expertise, tacit methods, and frontier problem-solving heuristics from their training environments into firms.
2. Capability augmentation: these graduates enhance the absorptive capacity and dynamic capabilities of organizations, enabling them to better assimilate and exploit external knowledge.
3. Network spillovers: through continued ties to mentors, collaborators, and elite research communities, graduates embed firms within high-status networks that provide early access to emerging ideas and collaborations.

The ATDF thus shifts attention from aggregate measures of human capital to the *lineage-based origins* of talent. This perspective is especially relevant for AI, where knowledge is tacit, rapidly evolving, and diffused through open but elite-driven scientific communities (Jordan & Mitchell, 2015; Lee & Schankerman, 2020).

Empirical Setting and Contribution

To test the ATDF, we assemble a novel dataset linking the career trajectories of approximately 22,000 graduates of elite AI scientists across ten subdomains to firm-level performance data from Compustat between 1990 and 2024. Our identification strategy exploits within-firm variation over time, examining how productivity changes when firms hire "immortal children" compared to control firms that hire graduates without such elite

lineage. Using fixed-effects regressions, we estimate the effects of genealogy-based talent acquisition on firm productivity.

The results reveal significant and persistent effects: doubling the stock of immortal children within a firm is associated with a 6–13 percent increase in total factor productivity (TFP), across heterogeneous specifications. These gains persist over multiple years and are evident across both digital-intensive industries (e.g., information services) and capital-intensive sectors (e.g., manufacturing).

Contributions to Economics and Strategy

This study makes four key contributions. First, we extend the human capital literature in economics and strategy by highlighting *academic genealogy* as a critical dimension of AI talent differentiation. While prior work has focused on the quantity or general quality of talent, we show that the lineage of training profoundly shapes the downstream impact of talent on firm outcomes.

Second, we extend the literature on AI, economics, and firm strategy by demonstrating that value capture from AI is not only about infrastructure, algorithms, or data, but also about the *lineage of individuals* who develop and deploy AI capabilities within organizations. This perspective aligns with recent work emphasizing the role of general AI talent in shaping firm performance (Babina et al., 2022; Brynjolfsson & McElheran, 2022).

Third, we provide actionable insights for managers and policymakers. For managers, the findings highlight the strategic importance of considering academic genealogy in hiring and talent development. For policymakers, the results underscore the importance of enabling the mobility of frontier AI talent and supporting mechanisms that expand the scale and scope of elite AI training.

Fourth, our methods in this paper are applied only to AI, but the general approach we use to connect elite academic talent to firm-level outcomes could be applied to any important emerging technology. We thus believe the paper provides a methodological approach that could be used to investigate the importance of this channel of knowledge flow in other technological domains.

In sum, this paper extends research on AI and firm performance by centering on the genealogy of talent. In doing so, it bridges literature on knowledge transfer, strategic human capital, and innovation, and offers a framework for understanding how frontier expertise travels from university labs to firms, which should be broadly applicable to technologies other than AI.

2. Literature Review and Theoretical Framework

The question of how firms acquire, deploy, and benefit from talent has long been central to economics and strategic management. Our work contributes to and extends several related streams of scholarship: (1) human capital and firm performance, (2) star scientists and knowledge diffusion, (3) organizational capabilities and innovation, and (4) the emerging literature on AI as a transformative technology. Building on these literatures, we emphasize academic genealogy as a mechanism of talent differentiation and analyze its impact through the AI Talent Diffusion Framework (ATDF).

2.1 Human Capital and Firm Performance

As artificial intelligence (AI) becomes increasingly central to organizational decision-making and value creation, understanding how firms acquire and mobilize AI capabilities has become a critical question for both scholars and practitioners. AI systems, ranging from machine learning algorithms to natural language interfaces and robotics platforms, hold the potential to transform not only operational efficiency but also strategic agility, innovation processes, and product-market positioning. However, despite widespread recognition of AI's disruptive potential, firms exhibit significant heterogeneity in their ability to deploy these technologies effectively. This performance variance raises important questions about the antecedents of AI capability formation, particularly the role of human capital in enabling firms to translate technological potential into sustained competitive advantage.

In our introduction, we noted how both the knowledge capital literature in economics and the strategy literature's resource-based view (RBV) of the firm provide a conceptual lens for examining these dynamics. In both these literatures, firms achieve and sustain superior performance by acquiring valuable resources. In the context of AI, these literatures suggest that firms that can access rare talent pools, particularly individuals with specialized expertise and access to frontier knowledge, are better positioned to outperform competitors.

Within these conceptual traditions, elite-trained AI talent represents a particularly potent resource. Graduates trained by the pioneers of AI, those who helped define and advance the foundational subfields of machine learning, natural language processing, robotics, and beyond, carry with them not only technical skill but also embodied cognitive models, scientific norms, and social capital acquired through their training. These individuals operate at the cutting edge of AI knowledge and are often tightly connected to global research networks, elite institutions, and high-impact innovation communities. As such, they are not easily substitutable by generalist technical staff or even by AI professionals without such pedigrees.

Yet, despite the growing consensus around the strategic importance of talent in technology adoption and innovation, the mechanisms through which AI-specific human

capital influences firm outcomes remain incompletely theorized and empirically underdeveloped. Prior research on university-to-industry spillovers has shown that hiring individuals from prestigious academic institutions can accelerate firm innovation by embedding tacit scientific knowledge and exposing firms to new cognitive frameworks and problem-solving heuristics (Zucker et al., 1998; Cockburn & Henderson, 1998). These studies highlight that academic background, and particularly proximity to elite research environments, can shape the absorptive capacity and innovative potential of firms. Following the insights generated in these papers, we argue that academic genealogy represents a unique and powerful form of human capital differentiation. Mentorship under elite AI pioneers ("immortals") is not merely a signal of intellectual prestige; it is a formative experience that embeds individuals within particular knowledge regimes, epistemic cultures, and innovation networks. These relationships shape how AI graduates think, solve problems, engage with evolving technologies, and interact with both academia and industry. By tracing the career trajectories of graduates trained by these mentors and examining the performance outcomes of the firms that hire them, we offer new insights into how the origins of human capital affect firm-level strategic outcomes in AI adoption and innovation.

2.2 Star Scientists and Knowledge Diffusion

A second relevant literature examines the role of star scientists in innovation and organizational performance. Zucker, Darby, and Brewer (1998) demonstrated that firms located near star bio-scientists enjoyed faster rates of biotechnology commercialization, highlighting the importance of tacit knowledge. Cockburn and Henderson (1998) showed that firms with strong university connections performed better in pharmaceutical innovation. Azoulay, Zivin, and Wang (2010) further established that the presence of star scientists can significantly influence the productivity of their colleagues and institutions.

These studies emphasize three key points. First, talent is not fungible: *who* a scientist is, and *where* they are trained, matters greatly. Second, tacit knowledge that is difficult to codify, often travels through people, particularly through close mentorship and collaboration. Third, the ability to access frontier science can be especially important in those contexts in which new scientific developments arise that are relevant – even transformative – for industrial innovation. The biotechnology revolution sparked by the emergence of recombinant DNA technology appears to have created exactly this kind of unusual proximity between frontier science and the needs of industry in earlier decades. We suggest that relatively recent developments in machine learning and AI have created a similar proximity between industrial R&D and academic science in these domains.

2.3 Knowledge Capital, Organizational Capabilities, and Innovation

The innovation and strategy literatures provide important frameworks for understanding how firms absorb and benefit from new knowledge. Three are particularly relevant:

1. Absorptive Capacity: Cohen and Levinthal (1990) argue that firms' ability to recognize, assimilate, and exploit external knowledge depends on prior related knowledge. Hiring immortal children increases a firm's absorptive capacity by embedding frontier expertise directly into its workforce.
2. Dynamic Capabilities: Teece (2007, 2018) emphasizes the role of dynamic capabilities—firms' ability to sense, seize, and reconfigure resources in response to changing environments. Immortal children strengthen dynamic capabilities by enabling firms to adapt rapidly to advances in AI.
3. Complementary Assets: Teece (1986) highlights that the value of an innovation depends on complementary assets such as manufacturing, marketing, and distribution. In the context of AI, these assets include data infrastructure, computing capacity, and organizational readiness. While these are necessary, our work suggests that elite academic talent is a *critical human complement* that allows firms to integrate such assets effectively.

2.4 AI as a Distinctive Context

AI represents a particularly important setting in which to study the impact of elite scientific talent. Unlike many other technologies, AI:

- Is widely viewed as a general-purpose technology (GPT) with applications across nearly all sectors (Brynjolfsson & McElheran, 2022).
- Relies heavily on tacit, rapidly evolving knowledge that is not easily codified in textbooks or training manuals (Jordan & Mitchell, 2015).
- Diffuses, in part, through elite-driven scientific/research communities where access to frontier ideas often depends on personal ties and mentorship (Lee & Schankerman, 2020).

These features heighten the importance of lineage. Graduates trained under elite AI mentors are not only technically skilled but are also embedded within networks that shape the diffusion of AI knowledge globally. Firms that hire these graduates tap into pipelines of tacit expertise and privileged networks that accelerate adoption and deployment.

2.5 The AI Talent Diffusion Framework (ATDF)

To consider the ways in which elite AI expertise flows from academia into firms, we use the AI Talent Diffusion Framework (ATDF), which highlights three interrelated mechanisms—

knowledge transfer, capability augmentation, and network spillovers— to explain how the academic lineage of AI talent can shape firm-level productivity and strategic advantage.

2.5.1 Knowledge Transfer

The first mechanism, knowledge transfer, captures the direct movement of codified and tacit knowledge from elite academic mentors to firms through their graduates. Immortal children—graduates trained under pioneering AI scientists—bring with them not only technical know-how but also exposure to the research frontiers of AI, methodological rigor, and conceptual frameworks shaped during their training. These graduates often operate at the cutting edge of subfields such as machine learning, natural language processing, robotics, and computer vision. When hired into firms, they act as *knowledge vectors*, embedding advanced ideas into organizational processes, products, and strategies.

This mechanism aligns with research on star scientists and knowledge diffusion, which shows that the mobility of elite scientists across institutional boundaries leads to measurable gains in innovation (Azoulay et al., 2010). Importantly, the knowledge carried by immortal children is not generic; it is frontier-specific, situated within evolving paradigms, and complex. It must be internalized through close interaction, a process catalyzed by the presence of elite-trained graduates within firms.

2.5.2 Capability Augmentation

The second mechanism, capability augmentation, explains how elite AI graduates strengthen firms' technological and organizational capacities. While knowledge transfer concerns the *content* of expertise, capability augmentation concerns the *application* of that expertise, how it enhances firms' ability to identify opportunities, solve complex problems, and adapt to rapid change.

Drawing on the notion of absorptive capacity (Cohen & Levinthal, 1990), we argue that graduates of immortal lineages equip firms to better recognize, assimilate, and exploit external knowledge. These individuals often bridge scientific discovery and applied engineering, serving as crucial translators between frontier research and commercial deployment. Beyond technical contributions, they also bring problem-solving orientations honed in elite academic environments, rigorous experimentation, scalable evaluation methods, and data-driven decision-making practices. Over time, these routines enhance firms' dynamic capabilities (Teece, 2007), enabling them to reconfigure resources and remain competitive in environments where AI technologies evolve rapidly.

2.5.3 Network Spillovers

The third mechanism, network spillovers, captures the relational and reputational advantages firms gain by hiring graduates from elite academic lineages. Unlike traditional hires, who bring only their individual expertise, immortal children connect firms to broader epistemic and innovation communities. These networks span co-authors, academic

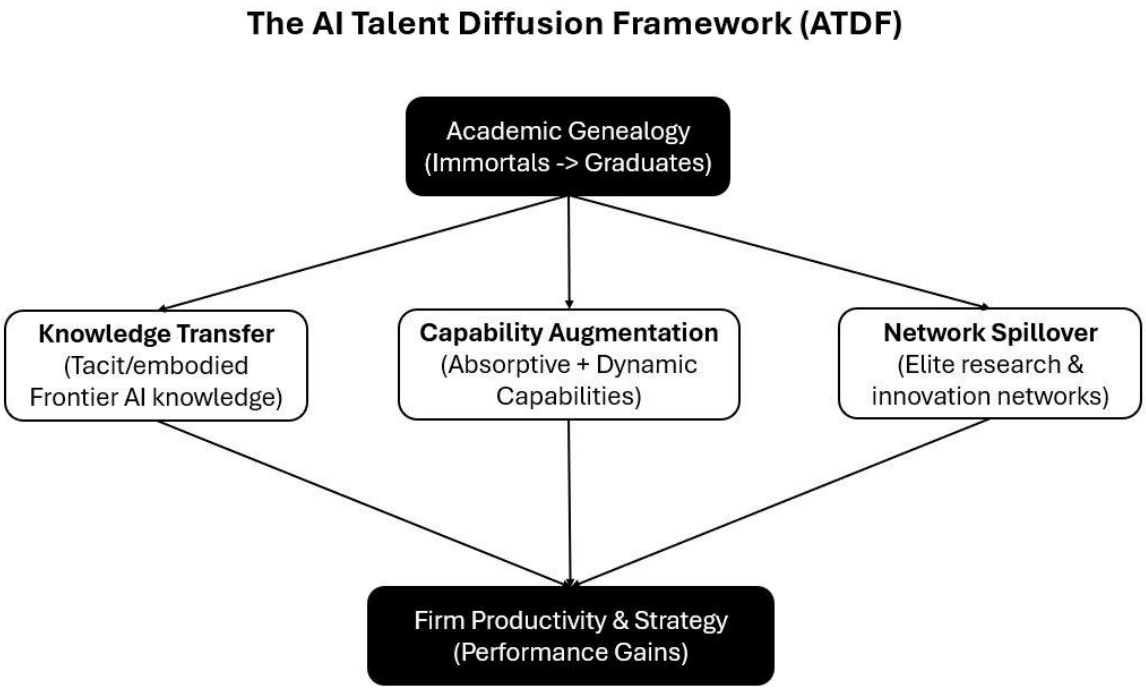
collaborators, government agencies, research consortia, and leading technology companies.

Through continued engagement in these networks, via publications, conferences, collaborations, and advisory roles, graduates create relational bridges that firms can leverage for strategic benefit. This resonates with research on inventor mobility and innovation networks, which shows that mobile talent carries access to siloed knowledge and facilitates recombination across organizational boundaries (Rosenkopf & Almeida, 2003). In the AI context, spillovers may take the form of early visibility into research breakthroughs, opportunities for cross-sector collaborations, or privileged access to public and private funding streams.

Critically, these advantages are not evenly distributed. They accrue disproportionately to firms employing graduates embedded in high-status academic lineages, and often persist even after individual employees depart. Firms known for hiring elite AI talent can develop reputations as innovation leaders, creating a self-reinforcing loop that attracts additional top-tier candidates and strengthens their position in the AI ecosystem.

Together, these three mechanisms, knowledge transfer, capability augmentation, and network spillovers, form a holistic model of how academic genealogy shapes firm performance. The ATDF moves beyond narrow accounts of individual productivity to emphasize the transmission of deeply embedded knowledge structures and relational capital through elite training lineages. It highlights that the impact of hiring AI talent is not uniform, but conditioned by the *quality and pedigree of training*.

By theorizing academic genealogy as a strategic vector of AI knowledge diffusion, the ATDF contributes to both the human capital and innovation literatures. It offers firms a lens to assess the long-term value of talent acquisition decisions and invites scholars to reconsider how the institutional origins of talent influence capability development and competitive advantage in knowledge-intensive industries.



The ATDF framework captures this genealogy-based flow of expertise and its interaction with firm-level absorptive readiness and ecosystem positioning. By shifting attention from general expert mobility to genealogical diffusion, the framework offers a more precise and falsifiable model of how AI talent shapes firm performance.

3. Empirical Gap and Research Question

While a growing literature investigates how AI adoption influences firm-level outcomes such as productivity, innovation, and profitability (Cockburn et al., 2018; Brynjolfsson & McElheran, 2022), most studies conceptualize AI as a technological or organizational capability, with limited attention to the origins and structure of the human capital that underpins it. The question of *who* drives AI capability inside firms—what kind of training, mentorship, and lineage their talent possesses—remains insufficiently explored..

This omission is especially consequential in the AI domain, where knowledge is rapidly evolving, highly tacit, and tightly embedded within global scientific networks. If certain firms consistently gain productivity advantages by hiring graduates trained by elite AI pioneers ("immortals"), it would suggest that academic lineage represents a distinct and underappreciated source of competitive advantage.

Accordingly, our study is guided by the following core research question:

Do firms that hire academic children of elite AI scientists experience superior performance and productivity outcomes?

This question directly operationalizes the central hypothesis of the AI Talent Diffusion Framework (ATDF): that the academic genealogy of AI talent materially affects firm-level productivity. By testing this proposition, we aim to advance the literature on strategic human capital from a focus on aggregate skill levels to a more precise account of how the *origins of expertise* shape firm competitiveness in the AI economy.

4. Data and Study Design

To empirically examine the strategic impact of elite AI talent on firm performance, this study integrates detailed data on academic genealogy, career trajectories, and firm-level outcomes. By linking graduates of elite AI scientists ("immortals") to publicly traded firms, we construct a novel panel dataset that allows us to analyze how the presence of lineage-based AI talent shapes organizational productivity and performance.

4.1 Data Sources

4.1.1 Identifying Top AI Scientists

The foundation of our analysis is a curated dataset of academic genealogy records that traces the mentorship lineages of AI scientists across ten major AI subdomains: machine learning (ML), natural language processing (NLP), robotics, computer vision, speech processing, autonomous agents, human–computer interaction, knowledge representation, information retrieval, and general AI.

We begin by identifying approximately 2,000 "immortals", pioneering scholars who represent the intellectual frontier of artificial intelligence. To do so, we draw on Elsevier's Scopus publication database, which comprehensively covers peer-reviewed scientific venues/ conferences from 1960 to 2024. For each AI subdomain (machine learning, natural language processing, robotics, computer vision, speech processing, autonomous agents, human–computer interaction, knowledge representation, information retrieval, and general AI), we compile a list of top-tier publication venues—for example, ICML, NeurIPS, ICLR, and AAAI in machine learning; ACL and EMNLP in NLP; CVPR and ICCV in computer vision.

For every author who has ever published in these venues, we calculate their h-index based on cumulative citation counts across their publication record within the subdomain. We then rank authors within each subdomain and designate the top 0.2 percentile as elite scientists. This procedure yields a set of roughly 2,000 scholars who combine extremely high scholarly impact with sustained contributions to their respective fields.

4.1.2 Matching Top Scientists to Their Graduate Students

Using this bibliometric foundation, we then map each immortal's academic genealogy by tracing their graduate students, identified through dissertation repositories (e.g., ProQuest), faculty webpages, and institutional records. This was an extremely labor-intensive process that took months of effort from an energetic team of RAs. Unfortunately,

there is no single data source that provides comprehensive coverage of these important relationships. Not all dissertations are archived in data sources like ProQuest; coverage varies widely depending on the university. Most universities do not maintain comprehensive, searchable data bases that link graduates to their advisers. As a consequence, our research team had to visit individual faculty member web pages and laboratory web pages to find these connections. This process results in a dataset of approximately 22,000 graduates ("academic children"), who constitute the empirical basis of our study. These individuals embody frontier AI talent and allow us to examine how elite training environments shape the diffusion of knowledge into firms. Importantly, they include both doctoral advisees and post-doctoral advisees. Because we were eventually seeking to examine the impact of graduates who move into U.S. firms, we have invested more effort in identifying the academic children of elite scientists based in North American academic institutions.

4.1.3 Scale of the Academic Genealogy Dataset

Table 1 provides a quantitative overview of the scope of our dataset across ten AI subdomains. First, the breadth of our coverage is extensive: approximately 2,000 are identified, with the largest concentrations in machine learning (320), natural language processing (208), robotics (160), information retrieval (459), and general AI - *not elsewhere classified* (534). These scholars are associated with nearly 460,000 papers, reflecting their centrality to the evolution of AI research.

Second, the academic genealogy component documents more than 30,000 children of immortal (22,000 US). To date, subfields such as robotics (6,222), machine learning (5,071), information retrieval (5,318), NLP (4607) account for substantial shares. Some subdomains (e.g., speech, IR, general AI) remain in progress, reflecting variation in archival coverage and ongoing identification efforts.

No.	Data point \ Domain	NLP	ML	Robotics	Agents	HCI	Speech	KR	CV	IR	(Other) AI
1.	# of Immortals	208	320	160	29	17	140	4	79	459	534
2.	# of journals/conference venues	722	79	17	58	18	12	32	80	146	55
3.	# of papers associated with immortals	50,414	74,165	56,476	9,362	4,451	36,396	873	33,509	89,490	103,988
4.	# of children of immortals identified/information tagged (so far)	4607	5071	6222	836	291	2130	57	2610	5318	3771
5.	Balance # of children of immortals (yet to be tagged)	0	0	0	0	0	2232	0	0	+ Currently Finding New Children	+ Currently Finding New Children
6.	# of direct Immortal-Corporate collaborative papers	8,553	16,026	4,582	665	987	6,859	30	4,301	12,047	7,112

Table 1: Counts of star scientists, student advisees, and direct collaborations between corporate labs and star scientists by AI subdomain

Third, the dataset also incorporates direct immortal–corporate collaborations. Over 60,000 coauthored papers are observed, including 16,026 in machine learning, 12,047 in information retrieval, and 8,553 in natural language processing. These collaborations provide an additional dimension of knowledge transfer, alongside the movement of academic children into firms.

Taken together, the table underscores the magnitude and richness of our dataset. It demonstrates both the depth of scientific influence exerted by elite AI scholars and the breadth of diffusion channels— academic children and corporate collaborations—that form the empirical foundation of our analysis.

4.1.4 Career Trajectories

To trace the mobility of these graduates into industry, we use career history data from Revelio Labs, which aggregates professional records from LinkedIn and other public sources. For each graduate, we record longitudinal employment histories including employers, job titles, industry affiliations, and tenure durations. This enables us to identify the exact year a graduate enters a particular firm, allowing us to construct time-varying measures of genealogical talent at the firm level.

Of course, these features of the data necessarily imply that graduates will only be captured in these data if they create a LinkedIn profile. The propensity for AI graduates joining U.S. firms to create these profiles appears to be quite high, and we are confident that we are able to trace the career trajectories of most of these graduates. In striking contrast, a large fraction of the mentees of China-based leading AI scientists could not be matched to LinkedIn profiles, reflecting the reality that LinkedIn does not play anything like the same important role as a recruiting tool in China that it plays in the U.S. To the extent that we wish to capture the impact of AI elite graduates on U.S. firms, this gap in the data

may be of second-order importance. A large fraction of AI scientists of Chinese ethnic origin who find employment in U.S. firms do so after graduating from a non-Chinese university (usually an American one).

While LinkedIn has become a widely used tool for recruiting in the U.S., there are still limits within that context. Older workers are perhaps less likely to create and update profiles, and worker flows that lie decades in the past are less likely to be accurately traced in these data. Given our focus on rising demand within industry for workers with highly specialized expertise, these limitations may also be of second order importance, since this increased demand is relatively recent.

4.1.5 Firm-Level Performance Data, Present and Future

Firm outcomes in the current draft are drawn from Compustat (1990–2024), a comprehensive dataset of publicly traded U.S. firms. We focus on measures that capture productivity and financial performance. These outcomes provide a multidimensional view of how genealogical AI talent contributes to firm performance. However, because Compustat only provides data on publicly traded firms, the important flows of elite AI talent into privately held firms (including AI startups) are not captured in these data.

Ongoing collaboration with researchers inside the U.S. Census Bureau will soon allow us to match our data on employment flows to the rich microdata maintained by the Census Bureau on all U.S. enterprises, including those that are not publicly traded. We anticipate that this expansion of our analysis could generate even stronger empirical results.

4.2 Study Design

To estimate the impact of frontier AI talent on firm performance, we build a longitudinal firm-level panel linking elite academic genealogy to organizational outcomes. This dataset allows us to analyze whether hiring graduates of elite AI mentors, academic children of "immortals", systematically enhances productivity.

Empirical Specification

We estimate a log-linear Cobb–Douglas production function of the form:

$$\log(Y_{it}) = \alpha.\log(K_{it}) + \gamma \log(L_{it}) + \delta \log(T_{it}) + Z`\theta + \mu_i + \lambda_t + \eta_s + \epsilon_{it}$$

Y_{it}: Firm output (Value added)

K_{it}: Capital input (estimated using Perpetual Inventory Method)

L_{it}: Labor input (employees)

T_{it}: Technological input — *AI patents* or *AI human capital*

Z : Controls (R&D expenses)

μ_i, λ_t, η_s: Firm, Year, and Industry (NAICS-2) fixed effects respectively

ϵ_{it}: Error term

Value added is calculated as operating income before depreciation plus labor expenses, net of intermediate inputs, deflated using the Consumer Price Index (CPI).

This framework captures the contribution of frontier AI talent to firm productivity while controlling for traditional inputs and firm-, time-, and sector-specific heterogeneity.

5. Results

Frontier AI Talent and Firm Productivity

Table 2 reports the results of the Cobb–Douglas regressions estimating the effect of frontier AI talent on firm value added.

VARIABLES	(1) value_added	(2) value_added	(3) value_added	(4) value_added	(5) value_added	(6) value_added	(7) 333-336	(8) 333-336	(9) 51	(10) 51	(11) 51
log_children_stock	0.279***		0.108***		0.102***		0.130***		0.0859***		
	(0.0154)		(0.00947)		(0.0108)		(0.0167)		(0.0294)		
L.log_children_stock		0.247***		0.0895***		0.0869***		0.110***		0.0721**	
		(0.0152)		(0.00981)		(0.0111)		(0.0174)		(0.0298)	
L2.log_children_stock											0.0621**
											(0.0300)
log_k_real			0.270***	0.309***	0.181***	0.209***	0.160***	0.191***	0.158***	0.174***	0.163***
			(0.00763)	(0.00885)	(0.0100)	(0.0120)	(0.0155)	(0.0185)	(0.0291)	(0.0351)	(0.0408)
log_emp			0.635***	0.615***	0.631***	0.623***	0.648***	0.634***	0.705***	0.689***	0.694***
			(0.00915)	(0.00972)	(0.0136)	(0.0143)	(0.0204)	(0.0212)	(0.0505)	(0.0550)	(0.0599)
log_xrd_real					0.132***	0.118***	0.141***	0.131***	0.0967***	0.0979***	0.0961***
					(0.00914)	(0.00954)	(0.0150)	(0.0157)	(0.0311)	(0.0332)	(0.0358)
Constant	3.981***	4.055***	2.215***	2.057***	2.239***	2.164***	2.099***	2.011***	2.336***	2.290***	2.354***
	(0.00427)	(0.00422)	(0.0272)	(0.0329)	(0.0363)	(0.0438)	(0.0534)	(0.0636)	(0.121)	(0.141)	(0.165)
Observations	65,996	61,724	63,581	59,399	41,955	39,267	19,300	18,065	5,216	4,833	4,461
R-squared	0.893	0.899	0.930	0.932	0.934	0.936	0.925	0.927	0.921	0.924	0.927

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Impact of Cumulative AI Children on Value Added

Magnitude of Effect: Across specifications, the estimated coefficients on the log of cumulative immortal children employed range from 0.086 to 0.279, all statistically significant. Interpreted as elasticities, these estimates imply that doubling the stock of immortal children in a firm is associated with an 8.6% to 27.9% increase in value added, holding capital, labor, R&D, and fixed effects constant. This effect is economically large, rivaling or exceeding the contribution of traditional R&D inputs.

Persistence of Effect: The inclusion of lagged variables reveals strong persistence: the first lag coefficient ranges from 0.087 to 0.247, while the second lag remains positive and statistically significant (0.062, $p < 0.05$). These results suggest that the benefits of hiring

frontier AI talent are not short-lived; they persist and compound as knowledge diffuses, teams adapt, and organizational capabilities deepen.

Industry Heterogeneity. To assess sectoral variation, we estimate models separately for advanced manufacturing (NAICS 333–336) and information services (NAICS 51). In both groups, coefficients on cumulative immortal children remain positive and significant.

- In NAICS 51 (information services), effect sizes are consistently larger, reflecting that digital- and data-intensive firms extract greater productivity returns from frontier AI talent.
- In NAICS 333–336 (manufacturing and transportation equipment), coefficients remain sizable but somewhat smaller, suggesting longer adoption and integration cycles in physical production environments.

Controls and Model Fit**:** The coefficients on the control variables behave as expected and are consistent with prior firm-level production function studies. Capital inputs show positive returns, with coefficients ranging from 0.149 to 0.309. Labor coefficients fall between 0.615 and 0.705, broadly aligning with theoretical expectations. R&D expenditures also display consistently positive and significant effects, with coefficients between 0.097 and 0.141, confirming that broader innovation investment remains an important driver of firm performance. These results provide a benchmark against which the magnitude of the frontier AI talent effects can be compared, and they reinforce the robustness of our empirical specification.

VARIABLES	(1) value_added	(2) value_added	(3) value_added	(4) value_added	(5) value_added	(6) value_added	(7) 333-336	(8) 333-336	(9) 51	(10) 51	(11) 51
log_children_stock	0.0749***		0.0883***		0.0902***		0.124***		0.0742**		
	(0.00939)		(0.00935)		(0.0107)		(0.0166)		(0.0290)		
L.log_children_stock		0.0644***		0.0762***		0.0781***		0.107***		0.0629**	
		(0.00978)		(0.00976)		(0.0111)		(0.0174)		(0.0298)	
L2.log_children_stock											0.0533*
											(0.0301)
log_k_per_emp			0.296***	0.340***	0.191***	0.225***	0.170***	0.205***	0.160***	0.180***	0.175***
			(0.00772)	(0.00867)	(0.00995)	(0.0116)	(0.0154)	(0.0179)	(0.0291)	(0.0348)	(0.0399)
log_xrd_per_emp					0.139***	0.122***	0.147***	0.136***	0.102***	0.102***	0.101***
					(0.00917)	(0.00957)	(0.0150)	(0.0157)	(0.0319)	(0.0341)	(0.0368)
Constant	3.006***	3.017***	2.035***	1.874***	2.146***	2.057***	2.014***	1.918***	2.307***	2.244***	2.279***
	(0.00316)	(0.00323)	(0.0253)	(0.0291)	(0.0335)	(0.0387)	(0.0495)	(0.0561)	(0.124)	(0.144)	(0.165)
Observations	65,942	61,675	63,581	59,399	41,955	39,267	19,300	18,065	5,216	4,833	4,461
R-squared	0.691	0.701	0.706	0.716	0.655	0.665	0.564	0.575	0.653	0.666	0.675

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Impact of Cumulative AI Children on per capita Value Added

Table 3 shows the results of regressions estimating the effect of cumulative immortal children on per capita value added, providing a direct measure of impact on labor productivity at the firm level.

Magnitude of Effect: Across specifications, the estimated coefficients on the log of cumulative immortal children employed range from 0.074 to 0.124, all statistically significant. Interpreted as elasticities, these results imply that doubling the stock of immortal children in a firm increases per capita value added by 7.4% to 12.4%, holding capital, R&D, and fixed effects constant. Compared to Table 1, the effect sizes on a per-worker basis are somewhat smaller but remain economically meaningful, underscoring the role of frontier AI talent in boosting productivity at the individual employee level.

Persistence of Effect: The inclusion of lagged stocks reveals notable persistence. The first lag coefficient remains positive and significant, ranging from 0.064 to 0.107, while the second lag also retains statistical significance in several specifications (e.g., 0.053, $p < 0.1$). This pattern indicates that the productivity contributions of frontier AI talent extend over multiple periods, consistent with a dynamic process where knowledge diffusion, worker learning, and organizational adjustment amplify the benefits of AI-trained graduates over time.

Industry Heterogeneity: To explore sectoral variation, we again analyze advanced manufacturing (NAICS 333–336) and information services (NAICS 51). Results reveal:

- NAICS 51 (Information Services): Effect sizes range from 0.062 to 0.180, with higher persistence coefficients, suggesting that digital and knowledge-intensive firms can integrate AI talent more rapidly and realize stronger per-worker productivity gains.
- NAICS 333–336 (Manufacturing and Transportation Equipment): Coefficients remain consistently positive (0.124–0.170), but somewhat smaller than in NAICS 51, reflecting longer integration cycles in industries reliant on physical production processes. These findings align with the broader narrative that the productivity payoff from frontier AI talent is heterogeneous across sectors, shaped by complementarities between human capital and sectoral technologies.

Controls and Model Fit: The control variables behave in line with theoretical expectations and prior empirical findings. The coefficient on capital per employee is positive and significant (0.170–0.340), indicating that firms with greater physical capital intensity experience higher per-worker output, though with diminishing returns. R&D expenditure per employee also displays robustly positive and significant coefficients (0.097–0.144). Across models, R-squared values range from 0.564 to 0.706, indicating strong explanatory power and providing confidence in the robustness of the specification.

Table 3 results demonstrate that frontier AI talent not only raises firm-level output (Table 1) but also enhances the productivity of individual workers. The effects are persistent,

economically large, and heterogeneous across industries, reinforcing the central argument that elite AI-trained graduates are a strategic resource with compounding productivity returns.

Overall, the results underscore the economic importance of frontier AI talent acquisition. Graduates trained under elite AI mentors appear to serve as catalysts for organizational learning, capability building, and the deployment of cutting-edge methods. Their impact is both statistically robust and economically meaningful, persisting across time and across industries.

These findings provide strong empirical support for the AI Talent Diffusion Framework (ATDF). They suggest that the diffusion of embodied frontier knowledge—via genealogical talent rather than codified inventions—is a critical determinant of firm competitiveness in the AI era.

6. Discussion and Conclusion

6.1 Theoretical Contributions

This study makes two primary contributions to the strategic management and innovation literatures. First, it refines the Resource-Based View (RBV) by offering a more differentiated understanding of human capital as a strategic resource. While prior work emphasizes the importance of talent for sustaining competitive advantage, our results show that the *academic lineage* of AI talent, specifically mentorship under elite AI pioneers, constitutes a unique source of value creation. Human capital is not homogenous; rather, it varies in its embedded knowledge, absorptive potential, and relational capital. Graduates trained under "immortals" carry embodied frontier knowledge and elite network ties that are rare, inimitable, and difficult to substitute, reinforcing RBV's central insights.

Second, the paper introduces the AI Talent Diffusion Framework (ATDF) as a novel theoretical lens for understanding how elite AI expertise transitions from academia into firms. The ATDF identifies three channels, knowledge transfer, capability augmentation, and network spillovers, through which genealogical talent enhances organizational performance. Our empirical findings strongly support these mechanisms: firms that hire graduates of elite AI scientists experience large and persistent productivity gains. By demonstrating that training pedigree matters, not just aggregate skill levels, the ATDF extends human capital theory and the knowledge-based view of the firm.

6.2 Managerial Implications

The findings hold important implications for managers and policymakers. For firms, they highlight the need to design hiring strategies that go beyond technical credentials.

Recruiting graduates of elite AI mentors disproportionately enhances organizational learning, accelerates the adoption of frontier methods, and improves productivity outcomes. Academic genealogy should thus be recognized as a meaningful signal of talent quality in recruitment and workforce planning.

For policymakers, the results point to the importance of facilitating the diffusion of elite AI talent across industries and regions. Initiatives such as targeted fellowship programs, support for academic–industry partnerships, and regional development grants can help expand access to genealogical AI expertise and reduce geographic disparities.

At the organizational level, the evidence underscores that the benefits of elite AI hires depend on absorptive readiness. Without complementary investments in data infrastructure, R&D processes, and cross-functional integration, even elite-trained talent may underperform. A strategic AI hiring agenda must therefore be coupled with organizational adaptation to unlock the full benefits of capability augmentation.

6.3 Methods and Data

This study also highlights data methods that could be broadly applied to other technological domains. In fact, we view them as a template that could be used to investigate the impact of immortal children far beyond the boundaries of AI. While our search for elite academic scientists focused on identifying the top researchers in AI, the publication data utilized in this study could in theory be applied to identify top researchers in any scientific field Similarly, the methods we have used to identify the graduate student and post-doctoral advisees of these top scientists could be used in other domains. Finally, the Revelio data utilized in our study could be used to track the movement of experts from academia to industry in any emerging technology.

6.4 Limitations and Future Research

Several limitations of this study point toward fruitful avenues for future inquiry. First, our dataset focuses on U.S. publicly traded firms in Compustat, which, while comprehensive for financial reporting, excludes private companies, startups, and small enterprises where much frontier AI activity occurs. This restriction may understate the broader economic effects of genealogical AI talent, particularly in early-stage or fast-scaling firms.

A key next step will be to expand the analysis using U.S. Census Bureau microdata, such as the Longitudinal Business Database and related establishment-level datasets. Census data provide far richer coverage than Compustat, capturing both public and private firms across the full size distribution. They also offer more detailed measures of employment, wages, establishment dynamics, and multi-unit firm structures. Leveraging Census microdata would not only extend the representativeness of our findings but also enable deeper investigation into how genealogical talent affects labor demand, wage structures, and intra-firm reorganization.

Second, the current focus on established firms leaves open the question of how academic lineage operates in entrepreneurial ecosystems. Graduates of elite AI mentors may be disproportionately likely to found or scale high-growth ventures, influencing the diffusion of frontier knowledge in ways distinct from large firms.

Third, as AI evolves, so too may the role of genealogy across subdomains. Future research could explore heterogeneity across emerging areas such as generative AI, causal inference, and AI ethics, identifying which subfields are most sensitive to lineage effects and why.

Finally, while our econometric design with firm and year fixed effects reduces bias, residual endogeneity cannot be ruled out. Future work could leverage natural experiments (e.g., immigration policy changes, research funding shocks) or qualitative methods to further sharpen causal inference.

6.4 Conclusion

In conclusion, this paper demonstrates that frontier AI talent transmitted through academic genealogy is a critical determinant of firm productivity and strategic advantage. Firms that hire graduates of elite AI scientists experience economically large and persistent productivity gains, reinforcing the importance of lineage-based human capital in shaping competitive outcomes.

By conceptualizing genealogy as a differentiated form of human capital, we contribute to theory, provide new empirical evidence on AI's impact on firms, and offer actionable insights for managers and policymakers. Firms that combine frontier AI talent with absorptive readiness are best positioned to translate research into results, while policy interventions that broaden access to elite-trained talent can promote more inclusive diffusion of AI's benefits across the economy.

References

Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press and NBER.

Agrawal, A., Gans, J., & Goldfarb, A. (2021). *Power and prediction: The disruptive economics of artificial intelligence*. Harvard Business Review Press.

Agrawal, A., & Henderson, R. (2002). Putting patents in context. *Management Science, 48*(1), 44–60.

Autor, D., Dorn, D., & Hanson, G. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review, 103*(6), 2121–2168.

Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics, 118*(4), 1279–1313.

Autor, D., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review, 103*(5), 1553–1597.

Azoulay, P., Graff Zivin, J. S., & Wang, J. (2010). Superstar extinction. *Quarterly Journal of Economics, 125*(2), 549–589.

Babina, T., Fedyk, A., He, A., & Dodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.

Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics, 122*(4), 1351–1408.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: 'Engines of growth'? *Journal of Econometrics, 65*(1), 83–108.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company.

Brynjolfsson, E., & McElheran, K. (2022). Data in action: Data-driven decision making and predictive analytics in US firms. *Management Science, 68*(8), 5850–5875.

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 23–57). University of Chicago Press.

Cockburn, I., & Henderson, R. (1998). Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. *Journal of Industrial Economics, 46*(2), 157–182.

Cockburn, I., Henderson, R., & Stern, S. (2019). The impact of artificial intelligence on innovation. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 115–146). University of Chicago Press.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.

Fry, C., & Glennon, B. (2024). In good company: Coethnic advisors and career paths of immigrant Ph.D. students. *NBER Working Paper 33782*. http://www.nber.org/papers/w33782

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal, 17*(S2), 109–122.

Griliches, Z. (Ed.). (1984). *R&D, patents, and productivity*. University of Chicago Press.

Hitt, M. A., Bierman, L., Shimizu, K., & Kochhar, R. (2001). Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective. *Academy of Management Journal, 44*(1), 13–28.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255–260.

Lane, J. I., Owen-Smith, J., Rosen, R. F., & Weinberg, B. A. (2006). The strength of academic lineage in generating prominent scientists. *Proceedings of the National Academy of Sciences, 103*(46), 17193–17198.

Mollick, E. (2012). People and process, suits and innovators: The role of individuals in firm performance. *Strategic Management Journal, 33*(9), 1001–1015.

Pakes, A., & Griliches, Z. (1984). Patents and R&D at the firm level: A first look. In Z. Griliches (Ed.), *R&D, patents, and productivity* (pp. 55–72). University of Chicago Press.

Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science, 49*(6), 751–766.

Waldinger, F. (2010). Quality matters: The expulsion of professors and the consequences for Ph.D. student outcomes in Nazi Germany. *Journal of Political Economy, 118*(4), 787–831.

Waldinger, F. (2016). Bombs, brains, and science: The role of human and physical capital for the production of scientific knowledge. *The Review of Economics and Statistics, 98*(5), 811–831.

Zucker, L. G., Darby, M. R., & Brewer, M. B. (1998). Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review, 88*(1), 290–306.