

**DYNAMIC DEMANDS VERSUS DURABLE SKILLS: CAREER DILEMMAS IN
PHARMACEUTICAL R&D**

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ABSTRACT

Skill demands evolve over the course of individuals' careers, as new roles demand different kinds of skills from previous jobs. Yet skill portfolios can be slow to change. We posit that this tension between dynamic job demands and durable skills creates career dilemmas for building the right portfolio of skills for long-term success. Studying a group of scientists in the pharmaceuticals industry, we argue and find that while specialization helps scientists advance faster initially, it holds scientists back once they reach managerial ranks where coordination skills are required. Within managerial ranks, scientists with broader experience will advance faster since their broad experience will develop broader knowledge and more diverse social capital, which in turn will help them build coordination skills. While we find some evidence that employees try to adapt to these changing needs over their careers, such efforts to adapt are insufficient. Instead, we find that the level of specialization acquired while working as a scientist continues to influence promotion rates after people are promoted into management. We thus show that a skill portfolio built to help advancement at one stage of the career may hold employees back at subsequent career stages.

INTRODUCTION

How do different kinds of skill investments contribute to long-term career success? Many people gauge career success using promotions, since those promotions are typically associated with higher compensation and status (Bidwell & Mollick, 2015; Ng, Eby, Sorensen, & Feldman, 2005). Human capital theory suggests that skills should be a crucial driver of those promotions, and that those skills are often acquired through on-the-job learning, accumulating over time to establish employees' eligibility for promotion (Becker, 1962; Mincer, 1962). Yet there are many different activities that employees might work on as they and their employers negotiate their task assignments, and many different skills that they might build. Among scientists, for example, the kinds of projects worked on shapes their portfolio of experiences; the right set of experiences is therefore important to long-term career success. Yet, we argue, crafting that optimal skills portfolio may involve a surprisingly difficult balancing act.

We suggest that identifying the right kinds of skill investments for long-term career success is difficult because of an inherent conflict between the durable nature of human capital investments and the dynamic nature of career demands. Human capital theory highlights the durable nature of investments in skills (Becker, 1964; Campbell, Coff, & Kryscynski, 2012), so that human capital acquired in one job continues to shape advancement out of subsequent roles. Yet career theory emphasizes that the nature of our work continues to evolve over our careers (Arthur, Hall, & Lawrence, 1989; Watkins, 2009), so that the kinds of skills that are valuable in one job might be very different from those that are useful in another. We argue that this tension between durable skills and dynamic job demands poses a dilemma in identifying the kinds of work that will help employees advance, as focusing on building the kinds of skills that help with

early-career advancement may then leave the employees with a sub-optimal skill portfolio for subsequent progression.

We examine how this dilemma shapes the careers of corporate R&D scientists. Scientific research requires the development and deployment of highly specialized scientific expertise, which must then be coordinated by managers in the service of organizational goals (Mahoney, 1979; Becker & Murphy, 1992). Common career paths in corporate R&D therefore take people through scientific roles early in their career and then into managerial roles subsequently (Gagliardi & Mariani, 2021). We argue that these different kinds of roles often benefit from the development of very different kinds of experience. Although studies of scientists suggest that increased specialization improves scientists' performance (Leahey, 2006, 2007; Wuchty, Jones & Uzzi, 2007; Jones, Wuchty & Uzzi, 2008), we theorize that working on a broader array of projects may better prepare scientists for the managerial roles they may enter later in their career, as a greater diversity of experience builds the kinds of knowledge breadth and diverse social capital that helps people coordinate effectively. We therefore suggest that the value of different kinds of experience depends upon the roles that people are in, complicating the process of assembling skills for long-term career success.

Specifically, we argue that working on a narrow set of technologies helps scientists win promotions early in their careers, as specialization aligns with the demands of their job, but that this same specialization may hold them back as they progress into managerial roles where broader knowledge and more diverse social capital will be required to coordinate work; within those managerial ranks, we suggest that it will be scientists with broader experience who will advance faster. Although scientists may seek to rebalance their experience as they change roles, the durable nature of skills means that the experiences gained earlier in the career have a lasting

effect on subsequent advancement. As a consequence, those who build the kinds of specialized experience that help them advance out of scientific roles will find that the same, specialized portfolio will slow down their advancement once they reach the managerial ranks.

We test these arguments using matched patent and LinkedIn data on scientists' careers in the pharmaceutical industry. Our results highlight the importance of match between the nature of the skills portfolio and the specific job, showing that promotion rates within scientific jobs are associated with having applied for patents within a narrower range of technologies, but that once people transition into managerial roles, further promotions are associated with having worked on a broader range of technologies. We also find that skill investments have durable effects, so that the portfolio of projects worked on as a scientist continues to affect promotions once people become managers, even though more specialized scientists broaden their portfolios once they become managers. The narrow human capital investments that help scientists advance through more junior positions therefore become a hindrance once those scientists enter managerial roles.

We intend this paper to contribute to the careers literature by highlighting the potential conflict between the dynamic nature of job demands during the career and the durable nature of human capital investments. Prior literature on careers has found benefits to specialization in some settings and to breadth in other settings, but does not generally explore *when* specialists or generalists on the same career path will thrive. We develop and test a coherent framework about when specialization or breadth will lead to career advancement. In doing so, we also highlight the way that different jobs on the same career paths reward different kinds of experience, creating acute dilemmas for employees. We show how the same sets of broad experience held by the same people can act as either a benefit or cost depending upon the kind of role that they are in, and that the benefit of having a particular orientation may be short-lived when we consider a

longer horizon of one's career. Last but not least, we contribute to research on scientists (Leahey, 2006, 2007; Uzzi, 2007; Jones, Wuchty & Uzzi, 2008; Roach & Sauermann, 2017; Nagle & Teodoridis, 2020). While there is significant research on scientists' skills and productivity, there is little research on the people who manage scientists. Existing work on scientific breadth shows how it helps scientists recombine knowledge to generate more novel inventions (Fleming, 2001 etc.); we extend this work by arguing that scientific breadth can also build managerial skills. We provide evidence on the kinds of experiences that help scientists advance into scientific management positions, as well as the experiences that help them continue to be promoted once they are in those managerial ranks.

THEORY DEVELOPMENT

Human Capital and Promotions

Promotions play a central role in modern careers. Usually defined as a move to a job in a higher hierarchical rank (Spilerman & Lunde, 1991), those promotions are a highly sought-after reward that often defines career success (Ng, Eby, Sorensen, & Feldman, 2005). Those same promotions also take people into jobs with more responsibilities, which can sometimes entail very different demands from those that the employee encountered in the past (Benson, Li, & Shue, 2019; Hill, 1992; Watkins, 2009).

A large body of research emphasizes the central role of performance in driving promotion decisions (Baek, Bidwell, & Keller, 2022; Benson et al., 2019; DeVaro, 2006). Employers usually seek to promote their most able performers because of the greater importance accorded to more senior roles (Williamson, Wachter, & Harris, 1975). The rewards associated with promotion further encourage employers to promote high performers, as doing so helps to motivate employees in the lower ranks (Lazear & Rosen, 1981). These pressures can sometimes

lead employers to promote high performers even though the skills and abilities that made them successful in their prior job will not help them to succeed within the new role (Peter & Hull, 1969; Benson, Li, Shue, 2019).

One critical attribute that shapes employees' performance – and therefore their promotion prospects – is the human capital that they possess (Becker, 1964). A core tenet of human capital theory is that people acquire human capital on the job, as they pick up skills through practice and repetition (Becker, 1964; Doeringer & Piore, 1971; Mincer, 1962). These theories emphasize that what people do shapes the skills they acquire.

The skills that people acquire from experience can also be very durable. While human capital can depreciate (Dinerstein, Megalokonomou, & Yannelis, 2022), research finds that the portfolio of experiences acquired over the career has enduring effects (Chattopadhyay & Choudhury, 2017). Hence, for example, studies have found that the cumulative diversity of areas that executives have worked in during their careers can shape their probabilities of being hired (Won & Bidwell, 2023), their compensation (Custódio, Ferreira, & Matos, 2013), and the strategic decisions that they make (Crossland, Zyung, Hiller, & Hambrick, 2013). Because these skills are durable, people's opportunities depend not just on what they are currently doing, but also on the set activities that they have performed in the past.

In this paper, we focus on a particular dimension of people's human capital – whether they acquire deep, specialized expertise by continually working within closely related fields, or whether they acquire more generalist experience through working in a broader set of areas. Note that this definition differs from some accounts of specialization which focus on whether the division of labor favors narrow jobs in which people work on a few tasks or broader jobs that comprise a wider array of tasks (e.g., Fahrenkopf, Guo and Argote, 2020). Our focus on whether

the set of experiences that people have moved through over time are similar to one another or more varied is consistent with many other studies of careers, including work by Ferguson & Hasan (2013), Won & Bidwell (2023), and Crossland et al. (2013). Prior research suggests that this breadth of experience is an important attribute of careers, shaping performance and advancement in a variety of contexts (e.g. Zuckerman et al 2003; Custodio et al, 2013; Crossland et al, 2013).

These narrow versus broad skill profiles are built up over time, reflecting the durable nature of human capital investments and the length of time that it takes to acquire deep expertise or broad experience. Yet the dynamic nature of careers means that skill profiles that might be a good match for the role at one point in the career may be very different from those that fit a subsequent role. In particular, we will argue that some career paths involve spending time working in specialist roles where deep, narrow expertise is valued, before transitioning into managerial roles that require the kind of broad skills that assist in coordination work. Although employees may seek to build new skills as the demands of their jobs change, those new skills take time to acquire. Hence, the durable nature of human capital means that the overall portfolio of skills acquired in the past – skills that might have been valuable for advancement in prior jobs – may no longer be well-suited for shaping advancement out of a current role. Ambitious employees may therefore face a dilemma between investing in the kinds of skills and experiences that will foster immediate advancement versus those that will aid promotion later in their careers.

In the rest of this paper, we seek to demonstrate this dilemma in the context of scientific careers. We demonstrate how the portfolio of experiences that fosters promotion changes as people move into more senior jobs, and how the set of experiences that help people get promoted into a job can then hinder their attempts to get promoted out of it.

Human Capital and Scientific Careers – the Tension between Depth and Breadth

Corporate scientists embody many of the characteristics of the modern knowledge worker. On the one hand, their careers revolve around the production of new knowledge. On the other hand, those careers take place within for-profit corporations, in which their investigations must be integrated with the broader goals of their employers. Quantitatively, corporate scientists make up a substantial group of employees, with many of the largest and most successful companies employing large numbers of research scientists, and entire industries such as pharmaceuticals and advanced electronics are based around developing and exploiting scientific advances (Arora & Gambardella, 1990; Agarwal & Ohyama, 2013; Sauermann and Stephan, 2013).

An important feature of the careers of corporate scientists (and of many other knowledge workers) is the transition over time from knowledge production to managerial roles. Perhaps because scientific work is seen as so expert-focused, organizations tend to prefer managers who have worked as scientists themselves and will therefore be able to understand the work being done. Gagliardi & Mariani (2021) note that: “leading a new-technology development team is different from ‘normal’ management. It requires fostering creativity while protecting the team from corporate interests” (p.5). Scientists themselves may also be more likely to take direction from managers whose scientific credentials they respect, while being more reluctant to follow those without a strong scientific track record. The unique demands of managing science therefore require many scientists to move over time from scientific work to managerial work, and many scientists see such moves as desirable to continue growing in their careers.

We focus on the kinds of on-the-job learning that might help scientists as they advance through these scientific roles and into management roles, focusing on whether scientists are more likely to advance if they have continually worked on projects within a narrow field of expertise,

or whether experience working on a broader variety of scientific questions leads to faster promotion. Initially, all scientists are “specialized” in that they only have experience in working in one area. As they progress across projects over time though, some of them will deepen that specialization by continuing to work in the same area, while others will broaden out, working on different kinds of projects. We explore how that difference between broadening out versus continuing to specialize over time shapes their career attainment.

Advancement in Scientific Jobs. As science has progressed, each generation of scientists has faced a higher ‘burden of knowledge’ that must be learned before they can make their own contributions to scientific advancement (Jones, 2009). This increased knowledge burden has led to greater specialization among scientists, allowing them to channel their attention to fewer fields, accumulating a related body of knowledge within a shorter time span (Becker, 1962; Rosen, 1972). Research on scientific productivity and careers suggests that scientists benefit from building very focused expertise, working continually on a narrow set of topics. Specialization can significantly improve skills, as deep experience assists with recall (Chase & Simon, 1973) and allows people to develop a more sophisticated understanding (Chi et al., 1988; Dane, 2010). Specialization can be risky as scientists’ expertise becomes heavily invested in a narrow research field whose prospects may decline over time (Hannan & Freeman, 1983). Moreover, specialization can be a barrier to embracing new ideas (Nagle & Teodoridis, 2020; Tong & Lee, 2024). Nonetheless, a substantial body of work suggests that specialization allows scientists to become more efficient at building expertise and thus more effective and productive (Leahey, 2006, 2007; Wuchty, Jones & Uzzi, 2007; Jones, Wuchty & Uzzi, 2008).

As noted above, organizations tend to promote people based on their performance. If a more focused portfolio of experience helps scientists to be more effective, we would expect

those who have acquired such specialized experience to be promoted at a higher rate. Working in a narrower set of areas should help scientists demonstrate stronger performance. We therefore propose that employers are more likely to promote specialized scientists when those scientists are in scientific roles:

H1: Specialization of scientific experience will be positively associated with the likelihood of promotions within scientific roles.

These arguments have implications for the skills that will foster transitions into managerial roles. As noted above, scientific careers often involve an eventual transition into management. Because scientists enter management by being promoted out of a scientific role, the kinds of factors that help people to be promoted as scientists – notably specialization of scientific experience – should help them transition into managerial roles.

It is worth noting that promoting more specialized scientists into management may not be optimal for the organization. As we develop below, there are grounds to believe that broader scientific experience may be a better fit with managerial work. Nonetheless, research on the Peter Principle emphasizes that promotions are usually based on how well employees perform in their current roles, not their fit with the role that they are being promoted into (Benson et al., 2019; Peter & Hull, 1969). Although organizations might do better to make promotion decisions based on how employees' skills match the demands of the future role, the challenges of assessing such fit lead them to default to promoting based on prior performance. Where specialized skills help scientists to demonstrate their ability and move more rapidly through scientific roles, those skills should therefore help them transition more quickly into their first managerial role. We therefore propose, as an important corollary to H1, that:

H2: Specialization of scientific experience will be positively associated with promotions from scientist to manager.

Advancement in Managerial Jobs. Although building human capital by working across a focused set of scientific areas is likely to help people perform better in scientific roles, we suggest that a broader portfolio may be a better fit with the requirements of managerial roles. While the heuristic that the employers use remains the same – promote people who are performing well in their current role – the experiences that help people in their roles change between scientific roles and managerial jobs. Consequently, we expect different kinds of experiences to predict promotion *within* the managerial ranks compared to the scientific ranks.

While scientific work often revolves around the development and deployment of highly specific scientific expertise, managerial work places a premium on coordination. According to Anderson and Bidwell (2019), "the central functions of managers are to plan, direct, and coordinate aspects of organizational activity, integrating the work done by others in the organization" (p.1001). As scientists move into managerial roles, they become responsible for supervising teams at various levels, coordinating across teams, liaising with representatives from many fields, managing projects, deadlines, and budgets, and charting future trajectories (Anderson & Bidwell, 2019). Such coordination work is particularly important given the way that modern scientific work is overwhelmingly performed within teams (Hart & Moore, 2005; Jones et al., 2008; Wuchty et al., 2007).

There are a variety of experiences that contribute to building such managerial skills; we propose that one important component of those experiences is having worked broadly across different areas of science. Specifically, we propose that broader scientific experience builds coordination skills through two mechanisms: breadth of knowledge and breadth of social capital.

There is evidence suggesting that the knowledge gained from working across broader scientific domains can help people coordinate with others (Teodoridis, 2018). First, those with

broader scientific experience are likely to have more knowledge overlaps with their colleagues. Mutually shared knowledge lowers coordination challenges by economizing on the need for explicit and formal mechanisms (Bechky, 2003; Puranam, Singh & Chaudhuri, 2009). Thus, broad scientific experience helps scientists become better coordinators than specialists.

Second, prior work shows that scientists who have worked across more scientific domains are more flexible in their problem-solving approaches (Teodoridis, Bikard & Vakili, 2019) and are able to utilize a broader set of knowledge, skills, perspectives and heuristics in their work than specialists are (Dunbar, 1995). Managers who coordinate multiple projects and teams are often required to be flexible and open to different approaches and ideas. Broad experiences enhance this flexibility and open-mindedness, fostering better coordination abilities.

Third, experience in more scientific areas helps scientists engage with unfamiliar knowledge – a skill that helps managers coordinate with other teams who come from different knowledge areas and have no overlap with their own. Broader experience implies that a broader and more diverse set of knowledge elements are “top-of-mind” for the individual, relative to specialized individuals who hold focused knowledge in the same domain (Bettis & Prahalad, 1995; Prahalad & Bettis, 1986; Chattopadhyay & Bercovitz, 2020). As a result, broad scientists are more in the habit of traversing multiple domains and engaging with distant areas even when these domains are relatively unfamiliar (Nagle & Teodoridis, 2021; Tong & Lee, 2024), and are more likely to perform the coordination or ‘bridging’ roles in a team (Melero & Palomeras, 2015; Teodoridis, 2018). For these three reasons, those with broader scientific experience are more likely to have acquired the coordination skills that are critical for effective managers.

The second mechanism through which breadth allows individuals to coordinate work more effectively is the accumulation of greater social capital. Scientists who have worked on a

broader set of scientific areas will build a wider network of collaborators (Stuart & Ding, 2006), developing greater social and relational capital (Byun, Frake & Agarwal, 2018). Each knowledge domain tends to consist of its own set of co-patenting collaborators so that, for example, the set of scientists researching how breast cancer propagates through pathways of cells tends to differ from the set that studies the environmental triggers of breast cancer. Diversifying into new areas is likely to bring new collaborators, broadening the scientists' social capital. Thus, those whose experience spans multiple domains are likely to have a larger and more diverse set of collaborators than specialized individuals working in fewer areas.

Social capital has been shown to be a valuable source of financial capital and knowledge (Burt, 1997; see Borgatti & Foster, 2003, and Hoang & Antoncic, 2003 for reviews of this literature), which can help generalists in their roles as coordinators across many projects. Research also shows that social capital helps coordination in roles where trust is important (Adler & Kwon, 2002) and that social capital is especially valuable for those who perform bridging and coordination roles (Burt, 1997), namely the managers. Therefore, while social capital is important for both scientists and managers, the benefits will be especially important in managerial roles where coordination is key. Broader networks should therefore be particularly valuable for people in managerial roles.

To summarize, working across a broad set of scientific areas can help people build broader knowledge and develop more diverse social capital, both of which will aid advancement once they are in managerial roles. Specifically, we suggest:

H3: Specialization of scientific experience will be negatively associated with a likelihood of promotions within managerial roles.

Durability of Skill Investments. A core contention of this paper is that changes in the skills portfolio required in different stages in the career create important dilemmas for managing

careers. We have argued that narrow experience aids promotion out of purely scientific jobs, while broader scientific experience is valued in managerial roles. These shifts in skill demands would not pose a dilemma where the relevant skills could be quickly acquired. If a rapid reorientation of a scientist's research portfolio allowed them to develop the experiences necessary to succeed as a manager, then they could simply build the skills necessary to succeed as a scientist while they are scientists, before pivoting to developing the kinds of skills needed to be a manager subsequently. They and their employers would not therefore face difficult choices as they considered what projects the scientists should be working on.

The durability of skill portfolios makes such rapid pivots difficult, though, as human capital accumulated long ago continues to shape career advancement and wages. Evidence for such durability can be found in the way that wages continue to grow with experience far into the career (Lagakos, Moll, Porzio, Qian, & Schoellman, 2017; Mithas & Krishnan, 2008), and how breadth of experience acquired throughout the career affects executives' employment prospects and pay (Custódio et al., 2013; Won & Bidwell, 2023). As a consequence, we argue that the nature of experience gathered while working as a scientist will continue to shape people's advancement even after they become a manager. Although those managers may try to broaden their experience to meet the demands of their new role, a substantial portion of their overall skill portfolio will represent skills that they developed while working in scientific roles; building that broader experience will therefore be a lengthy process, so that the skills that they built as scientists will continue to influence their careers.

A test of this career dilemma is therefore whether the portfolio of skills built as a scientist affects continued advancement once those scientists become managers, due to the durability of the human capital. Where such durable effects exist (as we hypothesize), it indicates that

scientists looking to advance face a difficult dilemma, where the kinds of experiences that will help them advance into management will slow down their advancement once they become managers. Where subsequent advancement depends only on the breadth of experience gained as a manager, scientists would face no such dilemma. We therefore seek to test the enduring effect of earlier skills investments with our hypothesis:

H4: Early scientific specialization (prior to promotion to management) will be negatively associated with promotions within managerial roles.

INSTITUTIONAL CONTEXT AND THE SCIENTIFIC CAREER LADDER

We study the careers of corporate scientists using data on inventors in the pharmaceutical industry. Those inventors are highly trained individuals, with the majority holding advanced scientific degrees. Due to the knowledge-intensive nature of the business, a large majority of managers and executives in these firms have scientific backgrounds.¹ The industry therefore offers a suitable setting to explore the interplay between dynamic demands and durable skills as individuals advance through the ranks.

Construction of the Career Ladder

We first used a manual approach to understand the scientific career ladder in the pharmaceutical industry. We manually examined career trajectories in inventor resumes and examined descriptions associated with job applications posted to Glassdoor. We followed these analyses with detailed conversations with three scientists employed in AbbVie, Bristol-Meyers Squibb, and Amgen. We then verified our construction of the career ladder using job postings data collected from the platform Indeed, that were run through a large language model (LLM).

¹ We study scientists within pharmaceutical organizations who are localized within the R&D divisions and are responsible for charting the medical strategy (among other tasks) of the organization at higher ranks. There are purely managerial tracks within pharmaceutical firms in operations, marketing, sales and supply chain, etc. These careers are outside the focus of this paper.

In examining the sequence of moves across the 4,794 job spells across our sample, we observed that pharmaceutical firms use very similar job titles, and 90% of the positions were captured by the following: *Scientist, Senior Scientist, Principal Scientist, Fellow, Senior Principal Scientist, Senior Fellow, Manager, Associate Director, Director, Head, Senior Director, Executive Director, Vice President, Senior Vice President, Executive Vice President and CEO*. After closely examining which position typically followed which position, we assigned numerical ranks to each position as follows: *Scientist* as a rank of 1, *Senior Scientist* as a rank of 2, *Principal Scientist, Fellow* as rank of 3, *Senior Principal Scientist, Senior Fellow, Manager, Associate Director* as a rank of 4, *Director* as a rank of 5, *Senior Director* as a rank of 6, *Executive Director* as a rank of 7, *Vice President* as a rank of 8, *Senior Vice President* as a rank of 9, *Executive Vice President* as a rank of 10, and *CEO* as a rank of 11.²

Note that our coding scheme accommodates the presence of partially separate promotion tracks for scientific versus managerial roles, which allow scientists to continue to be promoted without moving into managerial work. In particular, our analysis of trajectories found that people from rank 3 could either be promoted into scientific roles (Principal Scientist, Senior Fellow) or into managerial roles (Manager, Associate Director). Rank 4 therefore includes both scientific and managerial roles that are placed at the same hierarchical level. We did not, however, find additional scientific roles above this level that allowed for continued promotion.

Scientific vs. Managerial Roles in the Career Ladder

² Among the positions that were not assigned ranks (which was 10% of the total), the most frequently appearing title was *Leader* which accounted for 32.5% of the positions without a rank, followed by *Consultant* (23.2%), *Advisor* (9.32%), and *Specialist* (8.32%). We found it difficult to place these positions in the above scheme since the position appeared at various career stages. Hence, when an individual worked in a position without an assigned rank, we assigned a value that is *equal* to the previous job. Our results are robust to classifying these positions as one level *above* the previous job. In rare instances where the unassigned rank was the first position, it was assigned the same value as the next job. When the unassigned rank was the only role in the job history (n=3), it was assigned to the lowest rank of 1. Our results are robust to dropping those where the unassigned rank was the only role in the job history.

To examine how the nature of the scientific and managerial component roles changed along the career ladder, we analyzed job descriptions (Castilla & Rho, 2023; Zhang, 2023). We first read through a series of job descriptions from Glassdoor. These descriptions revealed how the nature of jobs evolves with seniority. For example, a job description for the position advertised for “Scientist, Clinical Pharmacology” with Johnson & Johnson in New Jersey lists a series of technical requirements.³ The job description of “Associate Director–Clinical Pharmacology & Pharmacometrics/ Oncology” at BMS in New Jersey, on the other hand, lists a series of tasks that are more managerial and strategic.⁴ Our inspection of these and other job descriptions indicated that managerial responsibilities were emphasized in managerial jobs, but did not constitute a significant part of scientists’ roles at ranks below that.

To perform a more systematic examination on how the nature of the scientific and managerial component roles changed along the career ladder,⁵ we also analyzed job descriptions posted by the 20 companies in our sample. We took these postings from Indeed,⁶ which aggregates postings from other platforms, company websites, job boards, etc.

We measured the proportion of scientific versus managerial responsibilities in these roles using ChatGPT, following other work that has used generative AI for analyzing large-scale text data (e.g., Carlson & Burbano, 2024; Chattopadhyay, Honore & Won, 2025; Chattopadhyay, Yu, Honore & Won, 2024). We downloaded 252 job postings posted by the 20 firms in our sample

³ Such as “[c]ontribute to overall compound development via application of quantitative methods to integrate knowledge of PK, PD, patient characteristics, disease states, and drug-drug interactions to optimize dose selection, dosage regimens and study designs throughout drug development. Working closely with the senior members, the Scientist will translate quantitative knowledge into strategic opportunities with key stake holders to drive development along the model-based drug development principles.”

⁴ Such as “[d]evelop strategies and lead worldwide health economic and outcomes research (WW HEOR) in support of Hematology asset indications” as well as “[d]evelop and execute innovative WW HEOR plans including real world data generation in support of Hematology assets” and “[s]ubstantial engagement with cross-functional internal and external collaborators will require a high level of technical leadership and communication skills.”

⁵ We thank an anonymous reviewer for suggesting this test.

⁶ Bright Initiative, a private company, provided access to all job postings that were made on Indeed between May 2022 and July 2024.

that were based in the scientific function (i.e., not in areas such as accounting, marketing, finance or supply chain) in any rank. Note that we were unable to find enough scientific roles in rank 4 to include in this analysis, and so our job posting data on rank 4 only includes managerial jobs.

More details of this data collection are reported in Section 1 of the Appendix.

We measured the scientific versus managerial content of those jobs using two complementary approaches. First, we used ChatGPT to infer the balance of scientific versus managerial *tasks* in each job posting, as described in Section 1, Part A of the Appendix. We then examined how the managerial component varied across the scientific and managerial job ranks. Figure 2 shows the boxplot of the managerial component by job titles, ordered from low to high rank. The X-axis displays the job titles, while the Y-axis is the proportion of the tasks described in the job posting that are deemed to be managerial. The proportion of managerial tasks was calculated as the number of managerial tasks divided by the sum of managerial and scientific tasks. The figure shows that lower ranks have a significantly lower managerial component and a higher scientific component. It also demonstrates a step-change in the managerial component of the job starting from rank 4 (Manager/Associate Director). Although jobs at lower ranks are higher on the scientific component and low on the managerial component on average, there is high dispersion at lower ranks as the job postings can include leadership-related terms in tasks such as “*mentor junior team members,*” or “*lead analysis.*” There is a lower dispersion in the managerial component of the job from rank 4 onwards, showing that the job descriptions are more similar to each other when firms advertise for managerial jobs.⁷

⁷ As a robustness check, we repeated the LLM analysis by reordering all of the job postings within the input file and found similar results. An alternative approach, based on scientific versus managerial *keywords* in the job posting (more details in Section 1, Part B of the Appendix), yielded similar results. Like the previous set of results, we found a step change in the occurrence of managerial keywords in rank 4, which is illustrated in the scatter plot in Figure 1A in the Appendix. From this analysis, we also plotted the occurrence of the words ‘manage,’ and ‘strategy’ by rank, as shown in Figures 1B and 1C in Section 1 of the Appendix. The figures show that the word ‘manage’ occurs infrequently in lower ranks, but much more frequently at

These analyses confirmed a shift from scientific tasks to managerial tasks as jobs become more senior. Notably, this shift is not linear across ranks, but rather involves a step change when people progress into rank 4 (Associate Director/Manager). Based on these findings, we coded jobs of rank 3 or below (comprising titles like *Scientist*, *Senior Scientist*, *Principal Scientist*, *Fellow*) as scientific jobs. Among jobs coded as a rank of 4, the job was considered managerial if the job included “Manager” or “Associate Director” in the title. All jobs coded as a rank of 5 (“*Director*”) or above are considered and coded as managerial jobs.

DATA AND METHODS

Testing our arguments requires us to gather data on corporate scientists’ degree of scientific specialization and career progress. We assemble such a dataset using two sources. First, we use patent application data from the United States Patent and Trademark Office (USPTO) to measure the kinds of technologies that scientists have worked on. We prefer to use patent applications rather than patent grants as more applications are filed than grants issued, providing a richer source of information about the kinds of expertise and knowledge that people will have gained from engaging in different projects. Discussions with pharmaceutical companies confirmed that appearing on a patent requires a substantial role in the knowledge production process. Our informants indicated that corporate lawyers meet with each patent applicant to evaluate their contribution, thereby minimizing gratuitous and token credit-sharing. Second, we used career history data from LinkedIn, a social media platform, to track career advancement.

We first took the entire roster of individuals who filed patent applications between 2000 and 2004 while employed at any of the top twenty (by volume of inventions) pharmaceutical

higher ranks, again with the break happening at rank 4. The word ‘strategy’ appears more frequently at rank 5 and above, indicating that strategy and decision-making tend to start when scientists achieve the title of Director.

companies (see Appendix Table B for a list). Since our goal was to examine the relationship between individuals' skills and career outcomes, we targeted the most productive pharmaceutical companies that employ large numbers of corporate scientists. We chose the years 2000 to 2004 as they are early enough for us to observe and track the full span of scientists' career trajectories while also ensuring that a significant portion have an online presence on LinkedIn.

From LinkedIn, we manually searched for each of these individuals using their names and firm names extracted from the patent application data. After identifying these individuals, we collected information on self-reported career history including the job title, employer name, start date, and end date of each job spell, as well as educational background such as the name of institution, year of graduation, major and the type of degree. Note that while we started with the top twenty pharmaceutical companies to generate our sample, our final data consists of the entire career history of the people in the sample as they moved in and out of these large pharmaceutical organizations; hence, there are a larger number of employers present in our data. Within our final sample, 85% of jobs were held within the top twenty pharmaceutical companies.

From the total of 4025 individuals on the patent application roster, we were able to identify 2151 individuals (53.4%) on LinkedIn. Among these profiles, we excluded 50.3% of inventors whose profile was sparse or incomplete, resulting in a sample of 1070 inventors with matched invention and career histories till 2021. From there, we further restricted the sample to those who filed applications for at least two patents prior to 2021, since we can only consider and measure the level of specialization once the individual applied for a second patent (more than one patent allows us to compare whether the patents are in the same area or not).⁸ Eventually, we were left with a sample of 945 individuals with matched inventions and career histories up until

⁸ We found qualitatively similar results when we included those with one patent. Results are available upon request.

2021. Note that while we used a window of 2000 to 2004 to construct the list of individuals, we used all of their patent applications prior to and after this window.

Although we believe that this combination of LinkedIn and patent applications provides the best insight into the careers of scientific workers, it may introduce some biases into our sample. For example, the sample of people who have posted public LinkedIn profiles may differ from the broader population. We explored this possibility by comparing several metrics between the broader universe of inventors registered with the USPTO and our sample. The comparison group was composed of those who patented during the same period (2000-2004) and applied for two or more patents in the same IPC classes as our sample. We observed that both groups exhibit similar levels of patent productivity (the mean number of yearly patents is 1.13 and the median is 0.95 among individuals in our sample and the mean is 1.00 and the median is 0.72 for others in the universe) and the number of forward citations (the average number of 5-year forward citations for each patent is 3.14 for individuals in our sample and 4.28 for others), indicating a comparable degree of activity and influence in the patent landscape. Most notably, the level of specialization was found to be similar across both groups. The average specialization among the broader universe of inventors was slightly higher, at 0.67 with a standard deviation of 0.27, compared to 0.60 (mean) and 0.22 (standard deviation) among individuals in our sample.⁹ Given the small magnitude of the difference, we conclude that our sample construction will not severely bias our estimates.

A further issue with using LinkedIn profiles is that they may be incomplete. Although the public nature of LinkedIn profiles makes it unlikely that people will misrepresent their experience, they may not record every job that they have held. For example, we found that many

⁹ These comparative statistics were captured within the USPTO data at the last observed patenting year (and before merging with data from LinkedIn); hence the mean and standard deviation do not exactly match those presented in Table 1.

of the career paths that we collected began at rank 3 or 4. Although this may partly reflect people with more academic degrees entering roles at higher ranks, it may also indicate that people were leaving some of their earlier jobs off their profiles. Although such omissions will prevent us from capturing some of the promotions that take place during our study, we do not believe that it should correlate with specialization in ways that would bias our results.

Second, our analysis is confined to those involved in patent production. Companies' strategies for knowledge production can vary widely, and some scientists may not work on patentable projects. The high level of patenting in our sample (on average, people patent once a year, and only 12% of our sample had only one patent) suggests that patenting may be common enough in these roles to mitigate biases caused by our omission of non-patenting scientists. It is also possible that the management roles that scientists progress into are sometimes occupied by people lacking the kind of scientific background that would lead them to patent.

Because our approach is to follow people through their careers and identify the factors that shape whether they are promoted, we do not need data on the entire risk set of people competing for promotion into each of these jobs. Our results could be affected by systematic differences in how specialization affects the career paths of patenting versus non-patenting scientists if there is a correlation between selection into our sample (through patenting) and residuals in our regressions. Our reliance on patents as a metric of specialization makes it difficult to rule out such challenges. We therefore caution that our analyses must be interpreted as illustrating the effects of specialization contingent on having patented.

Dependent Variables

Promotion. Promotion was coded as 1 if the individual experienced any upward change in rank (as defined in our career ladder section) in the subsequent year and 0 otherwise. Given

that promotions could happen both when moving jobs within companies and when people moved jobs across companies, we include promotions during moves between firms as well as within. Both types of mobility represent the kinds of career advancement that we explore in this study.

Transition to the first managerial job. This variable was coded as 1 if the individual moved into a managerial job in the subsequent year (as defined in our section on the career ladder), *and* it is the first managerial job that they took.

Independent Variables

Specialization. Following past conventions (e.g., Hall, Jaffe & Trajtenberg, 2001; Teodoridis, et al., 2019; Chattopadhyay & Bercovitz, 2020; Nagle & Teodoridis, 2020, among many others), the degree of specialization was calculated for each individual-year as the sum of squared shares of all inventions in each applied patent class up to each year t .¹⁰ We used the International Patent Classification (IPC) to identify the patent class of each patent (e.g., Gruber, Harhoff & Hoisl, 2013; Oxley & Wada, 2001). In the IPC system, the highest level contains eight sections from A to H, followed by two-digit classes. We define patent classes at this two-digit level. Since it typically takes a few years from the inception of the project until submitting the application, we did not lag this variable in our main analyses. This variable can range from close to 0 to 1, with higher values indicating a greater level of specialization. We also used a modified version proposed by Hall (2005) that corrects for small sample sizes and verified the consistency of our results using this alternative measure.

Note that this measure assesses specialization based on whether people worked on projects related to a narrow or broad set of knowledge areas. An alternative means by which

¹⁰ While a majority of patents are assigned with a single classification (63.2% of patents in our sample and 80% of patents in the universe of patents), some patents span more than one category. In such case, one category is assigned to be the “main” category (USPTO, 1992). For our analyses, we used the main category, but our results are consistent when measuring the diversification of knowledge using all categories that a patent spans.

scientists could attain breadth is by working on different kinds of roles within those projects. Unfortunately, we lack data on the tasks that people performed on each project. Our baseline assumption, though, is that people who have worked on projects dealing with a broader range of technological areas will have developed broader knowledge on average than those whose projects spanned a narrower range of technological areas.

Specialization at the time of managerial promotion. We captured the specialization at the time of managerial promotion as the specialization measured one year prior to the year of managerial promotion for all subsequent job spells.

Control Variables

The extent of specialization will depend in part on career stage, as people who have worked on more projects will have had more opportunities to broaden out the areas they have worked in. We therefore controlled for years of experience, experience squared, current rank, current tenure in the job, the cumulative number of applied patents, the number of past employers, and gender. We also controlled for whether the individual has an MBA degree to account for their preference for the managerial role or their managerial ability. We included year-fixed effects and firm-fixed effects to account for yearly variations in promotions as well as firm-specific promotion rates.

Analytic Approach

We test our hypotheses using discrete time survival analysis, which estimates the probability of promotion in the next year (e.g., Allison, 2014; Baek et al., 2023). Our unit of analysis is therefore a year spent on the job, and a “failure” event is a promotion occurring in the next year. We treat the final year that an employee is in the data as “right censored” because we do not know whether they will be promoted in the following year. Those observations are

therefore dropped from our analysis. We found qualitatively similar results when we used the piece-wise exponential model. We clustered the standard errors by individuals.

We emphasize that these analyses are correlational and unable to establish a causal relationship between specialization and mobility. Although we would ideally use an instrumental variable to identify the effects of breadth, we were unable to identify a variable that would influence the projects that scientists work on without potentially affecting their promotion prospects. We discuss alternative explanations for our findings with our results.

RESULTS

We begin by presenting some basic descriptive analysis. First, we explored the prevalence of mobility into management roles. We argued that moving into management is a common career path for scientists – but how many make this transition? We analyzed these moves using a Kaplan-Meier survival curve, presented in Figure 1. The Kaplan-Meier Curve plots the cumulative risk of promotion into managerial roles at each time point, where the unit of analysis time on the y-axis is a year. The curve demonstrates that transitions into management are common during all phases of the career within our sample, and that around half of scientists will be promoted into management at some point over a 30-year career. The curve therefore demonstrates that moving to a managerial role is not a rare career path for scientists (at least for those who have a presence on LinkedIn), consistent with our argument that firms require domain experts to drive their strategy and need to fill managerial roles with individuals who have previously worked in scientific roles.

Table 1 provides the means, maximum and minimum values, standard deviations, and correlations across all of the variables in our analyses at the individual-year level. The average length of a job spell is 7 years, and the number of promotions per year is 0.05 – the low

promotion rate reflects our conservative coding scheme for promotions described in the Methodology section.

Main Findings

Promotions within Scientific Roles. Our first hypothesis predicted that specialists are more likely to be promoted within scientific ranks. To test this hypothesis, we conducted a subsample analysis using job spells within the scientific ranks. We excluded observations with the highest scientific rank (4), which cannot be promoted to higher scientific ranks.

The results are reported in Model 1 in Table 2. We see that knowledge specialization is positively associated with promotion within the scientific ranks ($\beta=0.66$, $p=0.02$). According to this estimate, a one standard deviation increase in the level of specialization (0.21) increases the rate of promotion by 13.9%. This supports our prediction in H1.

Transition to and Promotions within Managerial Roles.

H2 predicts that knowledge specialization helps individuals enter the first managerial position. We test the hypothesis again using discrete time survival analysis. Since the goal of this analysis is to estimate the likelihood of entering the first managerial position, individual-year observations that follow a transition into management were not used for this analysis. The results are reported in Model 2 in Table 2. The positive coefficient on *Specialization* ($\beta=1.15$, $p=0.03$) suggests that a one standard deviation increase in the level of specialization is associated with a 24.2% increase in the likelihood of being promoted to the first managerial position, providing

support for H2.¹¹ We also find that MBAs are more likely to be promoted to a managerial position ($\beta=0.95$, $p=0.01$).¹²

We go on to test H3 and H4 about promotion within the managerial ranks. These hypotheses are tested within the subsample of observations that have already attained managerial status. The process of selection into this sample (i.e., promotion into the managerial ranks) could bias our results. For example, if more specialized scientists are more likely to be promoted (as we argued), then those generalist scientists that do make it to management may be particularly high ability. Such selection effects could generate a spurious relationship between being a generalist and mobility in management.

We address these selection concerns using a two-stage Heckman model (Heckman, 1976; Certo et al., 2016). The Heckman model corrects results in the second stage (here, promotion probabilities) for biases arising from the first stage selection process (here, who becomes a manager). Such models usually require an exogenous regressor in the first stage to correct bias from non-randomly selected samples. We used year dummies as our exogenous regressor. Our logic is that becoming a manager is overwhelmingly a one-way process: people move into management over time but rarely move back. Hence, later in our sample, there is a higher probability that somebody will be a manager compared to earlier. To ensure that we meet the exclusion restriction, our second stage controls for the share of individuals who got promoted in that year (accounting for over-time variation in promotion rates), but excluded the year dummies

¹¹ Interestingly, job tenure has a negative effect on probability of transition to managerial role. This likely reflects selection processes, as people who have not been promoted into a managerial role by a certain point become increasingly unlikely to be promoted in the future.

¹² We also conducted supplementary analyses to explore whether having an MBA changed the effect of specialization. Our analysis within senior managerial roles (rank 7 and above) revealed that the coefficient on the interaction term between having an MBA degree and specialization is positive ($\beta=3.04$, $p=0.08$), which suggests that the effect of diversification is reduced in the presence of an MBA degree and vice versa, indicating a substitution effect. This is suggestive evidence that having an MBA degree partially substitutes for diverse knowledge in our empirical analysis, as experience across multiple knowledge domains helps develop managerial capabilities similar to formal management education. Results are available upon request.

themselves. Holding constant the rate at which people are promoted within that year, the precise calendar year should be exogenous to whether those in managerial ranks are again promoted, once we control for their experience and time in job. We again use discrete time survival analysis and clustered the standard errors by individuals.¹³ We removed the observations with the highest rank (rank of 11) from the analysis since they are not at risk of further promotion.

Model 3 of Table 2 reports the first stage of the Heckman model. We plotted the coefficients on the year dummies in Figure A in the Appendix and see that they increase monotonically across years.¹⁴ In Model 4, we show the second stage where we can examine the effect of *Specialization* on promotions among the managerial ranks. Consistent with our prediction in H3, we see that the effect of *Specialization* is negative and statistically significant ($\beta=-0.31$, $p=0.04$), suggesting that a one standard deviation increase in *Specialization* is associated with a 6.5% decrease in the likelihood of promotion within the managerial roles.¹⁵

Durability of Skill Investments. We next tested our argument that the portfolio of experiences accumulated before entering managerial ranks will continue to shape promotion prospects after somebody becomes a manager. We tested H4 by breaking down the individual's level of specialization into their specialization at the time of managerial promotion and the change in the specialization level since the time of managerial promotion.

In Models 5 and 6 of Table 2, we again report the results from the Heckman model where the first stage estimates the probability of having transitioned to a managerial position

¹³ To implement this in a two-stage model, we use the package *heckprobit* in STATA 17.

¹⁴ The year dummies are jointly significant in predicting managerial promotion ($F = 3.19$, $p < .001$)

¹⁵ We further considered whether specialists and generalists might be disproportionately assigned to more important patent projects, potentially confounding the relationship between specialization and promotion. To address this, we incorporated multiple measures of project importance: forward citations (importance to the field), firms' self-citations (importance to the firm), and patenting in focal areas—the share of patents in a firm's core technological domains. Our main results remain largely robust. Further, we find modest evidence that working in strategically important areas weakly substitutes for specializing within scientific ranks and for diversifying within managerial ranks. Results are available upon request.

(Model 5), and the second stage estimates subsequent promotions (Model 6). We again clustered standard errors by individuals and removed the observations with highest rank (rank of 11) from the analysis. Model 6 shows that specialization at the time of the first promotion to manager has a significantly negative effect on subsequent promotions ($\beta=-0.35$; $p=0.02$), but the change in specialization does not ($\beta=-0.09$; $p=0.55$). This corroborates our prediction that the specialization of a scientists' knowledge portfolio may be hard to change even though individuals seek to adapt and diversify that portfolio after they transition into managerial ranks.¹⁶

We explored the possibility that the reduced effect of specialization after becoming a manager was caused by a lack of patenting in the managerial ranks. Descriptive analysis revealed that managers continue to patent at a rate that is at least as high as those in the scientific ranks, allowing their level of specialization to continue to evolve once they enter the managerial ranks. They therefore have the potential to evolve their portfolio over time, but experiences acquired prior to entering management continue to make up a substantial proportion of that portfolio.

We also examined whether scientists alter the patterns of skills that they acquire in response to the changing demands of the job. Specifically, we predicted the likelihood of applying for a patent in a new patent class to assess whether people have a greater propensity to diversify into new areas once they are in managerial roles. We found that people are more likely to diversify in managerial positions if they were previously more specialized, suggesting an increased effort to adapt. We share the details of our analytical approach as well as results in Section 2 of the Appendix.

Mechanisms

¹⁶ We also explored whether there were differences in the effects of specialization on internal versus external transitions. Unfortunately, only 10.8% of observations were external moves, making our attempts to distinguish the effects of internal and external moves relatively underpowered.

We conducted supplementary analyses to probe the mechanisms behind our findings.

The Role of Productivity. We argued that specialization is rewarded in scientific roles because it enhances scientists' performance. We explored this relationship by examining how specialization affects patenting (a common measure of scientific productivity), and how patents shape promotions.

First, we confirmed that specialization is related to increased patenting. We regressed the level of specialization at time $t-1$ on the number of patents at time t , controlling for the number of patents at time $t-1$ (see Model 1 of Table A in the Appendix). Consistent with our arguments, we found a positive correlation between prior specialization and subsequent productivity.

Second, we explored the relationship between patenting and promotion rates. In our main analysis of promotions within scientific roles (Model 1, Table 2), the confidence interval for the coefficient of patent counts included zero. We conducted follow-up investigations, exploring whether patents might have a non-linear effect on promotions. We did so by creating two spline variables, one capturing the range below a cutoff (we tried cutoffs at a count of 1 and at the 25th, 50th, and 75th percentiles) and the other capturing the range above. Results are presented in Table B of the Appendix. These analyses demonstrated a significant effect of patent counts on scientific promotions at low levels of patenting. This suggests that patent counts serve as a more salient signal of performance and quality for scientists with fewer patents, but the marginal effect diminishes beyond a certain threshold of patenting. As expected, we do not observe a similar pattern in the analysis of promotions within managerial roles (Table C of the Appendix), where a broader set of factors besides productivity likely influences promotion decisions. These analyses therefore support our argument that specialization aids promotion in the scientific ranks by increasing productivity.

The Role of Social Capital.¹⁷ We argued that one of the benefits of working in a broader set of scientific areas is that it allows individuals to build a wide network of collaborators, developing social capital that will aid them as managers. To test this idea, we collected information from PatentView on scientists' collaborators, using patents that listed only one assignee (95% of patents from our sample) to capture internal collaborators. For each collaborator, we identified their main scientific area (IPC class) based on the area with the highest running count of patents. We then calculated the diversity of collaborators for each focal individual by counting the number of unique primary areas across all of their collaborators. This measure, *collaborator diversity*, was calculated cumulatively for each year, using the running roster of collaborators.

We first confirmed that the breadth of projects is positively correlated with collaborator diversity ($\beta=-0.99$, $p=0.00$ in OLS regression, see Model 2 of Table A in the Appendix). We then included collaborator diversity in models predicting promotion (Table D in the Appendix). Although collaborator diversity does not significantly predict promotions within scientific roles (Model 1) or promotion to the first managerial position (Model 2), it does have a positive effect on promotions within managerial roles (Model 4), consistent with our arguments that social capital will benefit managers. Including this variable also slightly attenuates the effect of specialization (from $\beta=-0.30$ in Model 4 of Table 2 to $\beta=-0.26$ in Model 4 of Table D). This set of results supports the role of social capital as a mechanism relating broad experience to managerial promotions. We also found qualitatively similar results when using the number of collaborators (Models 5 to 8 in Table D) in place of collaborator diversity.

¹⁷ We thank anonymous reviewers for suggesting this test.

*Scientific Breadth and Managerial Competence.*¹⁸ We also explored the relationship between scientific breadth and managerial competence, using a survey experiment composed of promotion decision tasks. The experiment allows us to explore whether lay beliefs link scientific breadth with managerial ability. Note that this approach is not directly analogous to the promotion decisions observed in our sample, which are based on a broader evaluation of scientists' prior performance. Nonetheless, we aimed to bolster our arguments by demonstrating that a cross-section of observers also associates scientific breadth with managerial ability.

We recruited 100 participants through an online survey platform in Spring 2025. We restricted the sample to people who were in the labor force, over 25, and held a graduate degree, in order to identify a population that could more effectively evaluate scientific experience.¹⁹ In the experiment, participants assumed the role of senior decision-makers in a fictitious pharmaceutical company. Participants were presented with side-by-side candidate profiles competing for promotions (see Exhibit 1 in Section 3 of the Appendix). Each profile included structured information about the candidate's level of education, work experience, the number of completed projects, and the scientific domains of those projects along with fictitious patent numbers and titles for those projects. We asked respondents to evaluate the candidates for three types of promotion decisions: (1) Scientist to Senior Scientist, (2) Principal Scientist to Associate Director and (3) Associate Director to Director. For each promotion decision, respondents were also provided with a description of the role.²⁰ The experimental manipulation focused on the

¹⁸ We thank the anonymous reviewers for suggesting this study.

¹⁹ Specifically, we used a Prolific sample in which we restricted the participants to those who reside in the United States, possess at least a Master's degree, are fluent in English, are currently employed or actively seeking employment, and are 25 years of age or older.

²⁰ The role descriptions were stated as follows: "A Senior Scientist will lead experimental design and execution, contributing to drug discovery, research or development." "An Associate Director will oversee scientific teams and project portfolios, integrating cross-functional input to advance drug candidates while managing timelines, budgets, and strategy." "A Director will set strategic direction for research or development programs, leads teams, and aligns scientific goals with organizational priorities and regulatory expectations."

breadth of scientific experience, where projects for one candidate spanned multiple cancer areas while projects for the other candidate were focused in a single area. The level of education, work experience, and the number of projects were held constant (and gender and race of candidates masked). We also randomized the order of the profile shown (the order of the specialist vs. generalist for each promotion decision as well as the sequence of promotion decisions), so that any differences in skill perception or promotion outcomes could be causally attributed to variations in the breadth of scientific experience. Participants were asked to recommend one or other of the profiles for promotion.

The results of the promotion decision are plotted in Figure 3A in Section 3 of the Appendix. We found strong evidence that respondents linked scientific breadth with managerial capability, as they were more likely to recommend broader candidates when roles had a stronger managerial component. Candidates with broader scientific experience were significantly more likely to be recommended for promotion to Director (76% vs. 24%, $X^2=54.08$ ($p<0.00$)) and promotion to Associate Director (67% vs. 33%, $X^2=23.12$ ($p<0.00$)), but not for promotion to Senior Scientist (56% vs. 45%, $X^2=2.40$ ($p<0.12$)). The proportion of generalist recommendations was significantly different between promotion to Senior Scientist vs. Associate Director ($t=-2.46$; $p=0.02$) and Senior Scientists vs Director ($t=-3.76$; $p=0.00$); and marginally significant between promotion to Associate Director vs. Director ($t=-1.81$; $p=0.07$).²¹

At the end of the survey, we also showed the participants a series of statements regarding broad scientific experience and managerial capabilities. We asked these questions at the end of the survey so that the respondents were not cued to think about the purpose of the study when

²¹ We did not provide respondents with additional information about whether the areas the candidates worked on were strategically important areas. It is possible that respondents inferred the importance of those areas on their own, but we believe this is unlikely to have systematically affected the results.

they were making promotion decisions. Participants indicated their level of agreement on general statements such as “*Working across a wide range of projects cultivates communication skills, compared to focusing on projects within a narrow area.*” A large proportion of respondents (81.46%) either agreed or strongly agreed across four key managerial dimensions: communication, coordination, decision-making, and leadership skills. Respondents also rated generalists more highly in terms of technical skills (included as a comparative skill, valued in both managerial and non-managerial roles), but the proportion of those that agreed or strongly agreed was significantly lower compared to other managerial skills (64.65%).

It is important to emphasize that this experiment does not fully capture the mechanisms that we proposed for our main analyses. Drawing on the Peter Principle, we suggest that promotions largely reflect prior performance, rather than perceptions of competence. Hence, we argue and find that specialists are more likely to be promoted into the Associate Director role (reflecting their higher productivity), while our survey respondents favored generalists for this role. Nonetheless, our survey experiment does provide broader support for the relationship between scientific breadth and managerial capabilities.

DISCUSSION

Skill demands evolve over the course of their careers, as new roles demand different kinds of skill from previous jobs. Yet skill portfolios can be slow to change, as previously acquired experiences continue to play an important role in shaping people’s human capital. We posit that this tension between dynamic job demands and durable skills can complicate the process of building the right portfolio of skills for long-term success.

Studying a group of scientists in the pharmaceuticals industry, we argue that the value of specialized skills changes as people climb the organizational hierarchy, as specialized work done

by scientists needs to be integrated by managers with broader skills. We draw on these arguments to show that developing specialized skills will have different effects on promotion at different stages of scientists' careers, facilitating advancement early in the career but inhibiting advancement once they transition into managerial roles. There is some evidence that managers and their employers try to adapt to these changing needs, as managers who would most benefit from greater breadth are more likely to enter new technological areas. We find, however, that such efforts to adapt are insufficient. Instead, the level of specialization acquired while working as a scientist continues to influence promotion rates after people are promoted into management. Our analyses therefore highlight a dilemma for scientists' career progression, as a skill portfolio that helps advancement at one stage of the career may hold them back subsequently.

Contributions

Our paper contributes to the literature on mobility and human capital (Bills, 1988; Campion et al 2022; Bidwell & Keller, 2025; Ng, Eby Sorensen Feldman 2005; Ferguson & Hasan, 2013, among others), by identifying dilemmas that accompany investments in human capital. We highlight that the multidimensional nature of human capital creates dilemmas around how to make successful investments, as investments that may help advancement out of earlier jobs may hinder advancement out of later ones. Some prior research has highlighted the long-term implications of past experiences for future performance and behavior (e.g., Tilcsik, 2014; Chattopadhyay & Choudhury, 2017; Barbulescu & Bonet, 2023). We build on this stream of work by highlighting how those long-term effects can lead to dilemmas, as skills acquired earlier in careers inhibit advancement when individuals transition to new jobs. In this way, we show how the durable nature of skills means that experiences that may be helpful early in the career may be counterproductive subsequently.

We also add to the developing literature on specialists and generalists. Specialization has been traditionally associated with greater career success (Ferguson & Hasan, 2013; Leahey, 2007), although more recent studies have also found benefits for generalists (e.g., Merluzzi & Phillips, 2016; Leahey, Beckman & Stanko, 2017; Byun & Raffie, 2023). Although these mixed results suggest that the benefits of specialist versus generalist skills may be context-dependent, prior studies have not generally examined when specialist skills will be more likely to lead to promotions, or shown how context changes the effects of specialist skills over the span of individuals' careers. Zuckerman et al.'s (2003) study of actors documented that a focused identity is beneficial early in one's career but can constrain opportunities later on. Our work complements theirs by showing that, in a scientific context, different skills are rewarded in different roles. We highlight that diversified skills help scientists manage a wider range of projects and also acquire social capital which helps them coordinate and manage other scientists better. We hope that this paper generates deeper engagement in the question of when specialist versus generalist skills are more likely to confer career benefits.

Our paper also relates to literature on the Peter Principle (Peter & Hull, 1969; Benson, Shue & Li, 2019). Where the Peter Principle literature primarily focuses on performance, detailing how people who perform well in a lower-level role may perform worse in a higher-level role, we instead examine determinants of promotion. Nonetheless, we share with this literature an interest in the effects of changing job demands as people advance along career ladders. Because people may have limited control over their abilities, much of the discussion of the Peter Principle is based on the idea that traits that are good for performance at one level may not be effective at a higher level. We complement that work by exploring how changing job demands also affect fit with skill investments. Because skills are shaped by the investment

decisions that people make over time, changes in the value of different skills across the levels of a hierarchy suggests a need for forethought in how people plan out their careers and focus their skills investments.

Limitations

We acknowledge a number of limitations to this study. First, we cannot claim strong causality in our estimation methodology. Because we lack random assignment to specialist versus generalist research portfolios, our analyses are subject to endogeneity concerns. It is likely that scientists' research portfolios are shaped by a combination of the scientists' interests, organizational needs, specific opportunities, and strategic attempts to build valued skills (Stern, 2004; Sauermann & Cohen, 2010; Roach & Sauermann, 2017; Nagle & Teodoridis, 2020). One concern about our results is that the level of diversification could be related to unobserved underlying ability or interests in a way that might affect our results. For example, it could be that greater ability both allows scientists to work across more diverse areas and to perform better as managers. Alternatively, employers might prescribe a particular set of projects for high-fliers, or people interested in management might choose to construct a particular kind of portfolio. Such selection-based stories are difficult to reconcile with our results which highlight how the relationship between breadth and promotion switches signs as people advance. If breadth of experience reflected higher skill or predilection for management, it should consistently predict promotion across roles. Instead, we see that specialists are more likely to be promoted as scientists – including into a managerial position – but are less likely to be promoted as managers.

Second, we do not have access to performance data; hence we rely on the well-established link between performance and promotion in existing research (e.g., Benson et al., 2019). We were able to find a relationship between productivity and promotion at low levels of

patenting, but more robust data on performance would be helpful. We also lack data on the tasks that people performed within projects, relying instead on the differences between projects to assess individuals' accumulation of specialized or broader experiences over time. Our baseline assumption is that people who work across projects that span more scientific areas will develop greater breadth. Future research, perhaps using internal organizational data that provided more insight into team roles and individual performance, would usefully complement our study.

Lastly, our analyses use data on patenting scientists who have worked in large pharmaceutical companies, and it is unclear how they might generalize beyond that sample. Our theory is based on the idea that people must first establish their expertise in a field before they can manage work within that field, and that managerial work requires the ability to coordinate activities. Those conditions are most likely also to apply to the kinds of knowledge-intensive work that often takes place within large organizations. Fields such as engineering, medicine, law, and academia also require that managers be able to demonstrate the kinds of expertise that come from having worked as an individual contributor in the field. We would expect to see different dynamics in fields where managers do not need to demonstrate extensive domain expertise and can instead be hired out of MBA programs and other venues.

Practical Implications

We hope that our work can provide useful guidance for individuals and organizations. For individuals starting scientific careers, it is important to be mindful of the long-term consequences of early career choices. While certain experiences may not seem useful in the short term, individuals should consider acquiring skills and experiences that will be valuable later on, when their roles evolve. Organizations can help facilitate transitions by providing opportunities and resources, especially for managers with highly specialized experience as scientists. This can aid

them in preparation for responsibilities that require broad experience and skills. These endeavors can help enable effective career transitions, potentially leading to improved innovation outcomes.

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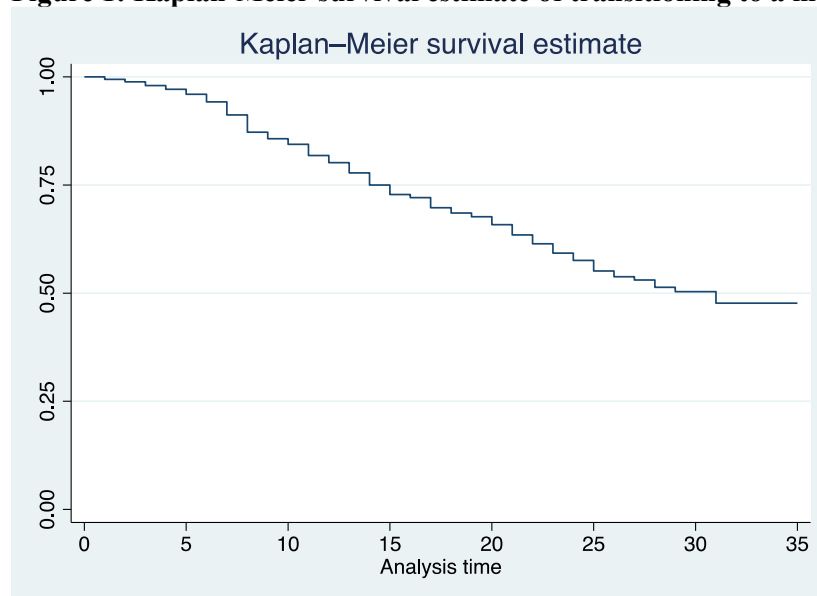
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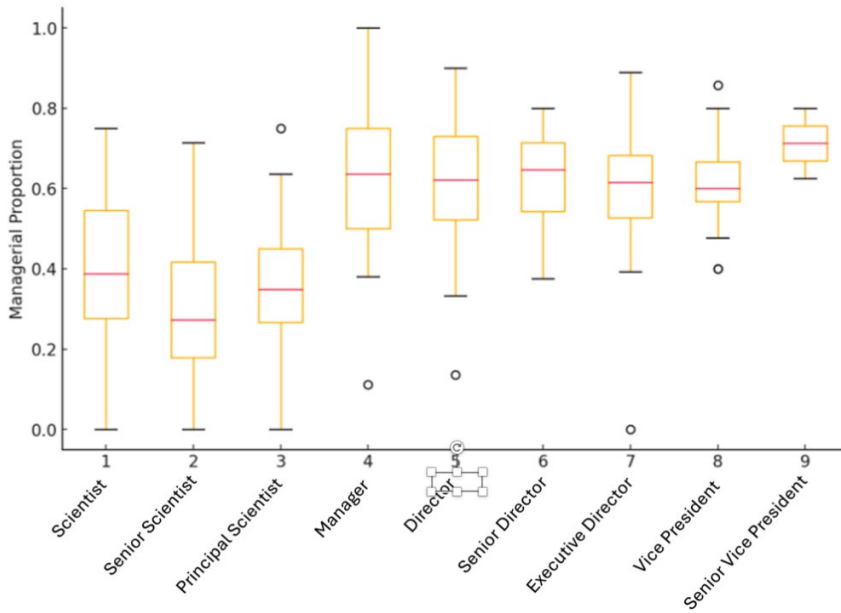
FIGURES AND TABLES

Figure 1: Kaplan-Meier survival estimate of transitioning to a managerial role



Note: The unit of analysis time is a year. The above graph plots the cumulative risk of having been promoted into a managerial role by a given point in time.

Figure 2: Box Plot Distribution of the proportion of managerial tasks within job descriptions by Rank



Note: Displayed along the x-axis are the job titles and associated ranks. The Y-axis represents the proportion of the tasks within the job that are coded as managerial.

Table 1: Descriptive statistics at the individual-year level (n=16,785)

	Mean	S.D.	1	2	3	4	5	6	7	8
1 Promotion	0.05	0.22	1.00							
2 Specialization	0.53	0.21	0.01	1.00						
3 Rank	5.47	2.29	-0.05	-0.07	1.00					
4 Job tenure	7.05	6.23	-0.05	-0.15	-0.08	1.00				
5 Experience	16.44	8.25	-0.03	-0.21	0.14	0.45	1.00			
6 # of employers	1.96	1.19	0.07	-0.06	0.14	-0.27	0.19	1.00		
7 # of patents	13.32	15.31	0.00	-0.33	0.16	0.22	0.23	0.02	1.00	
8 Female	0.15	0.36	0.02	0.04	-0.01	-0.04	-0.03	0.04	-0.12	1.00
9 MBA	0.04	0.19	0.04	0.07	0.03	-0.09	-0.05	0.13	-0.07	-0.02

Table 2: Estimation of promotions using discrete time survival analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Promotion within scientific roles	Promotion to first managerial position	Transition to managerial role	Managerial promotions	Transition to managerial role	Managerial promotions
Specialization	0.66* [0.02]	1.06* [0.04]	0.45* [0.04]	-0.30* [0.05]	0.45* [0.04]	
Specialization at the time of managerial transition						-0.35* [0.02]
Change in specialization since the time of managerial transition						-0.09 [0.55]
Job tenure	-0.02	-7.61*	-0.05**	0.00	-0.05**	0.00

Experience	[0.18] -0.03 [0.24]	[0.02] -0.03 [0.48]	[0.00] 0.02 [0.24]	[0.43] 0.05** [0.00]	[0.00] 0.02 [0.22]	[0.69] 0.07** [0.00]
Experience squared	0.00 [0.38]	0.00 [0.73]	0.00 [0.15]	-0.00** [0.00]	0.00 [0.12]	-0.00** [0.00]
# of past employers	0.20** [0.00]	0.05 [0.57]	0.09+ [0.06]	0.03 [0.20]	0.09+ [0.06]	0.05** [0.01]
# of patents	0.00 [0.68]	0.02+ [0.09]	0.01 [0.18]	0.00 [0.63]	0.01 [0.20]	0.00 [0.79]
Female	0.13 [0.45]	0.18 [0.52]	-0.09 [0.52]	0.05 [0.47]	-0.10 [0.51]	0.07 [0.24]
Rank	-0.06 [0.41]	2.68** [0.00]	0.74** [0.00]	-0.08** [0.00]	0.74** [0.00]	-0.08** [0.00]
MBA	0.16 [0.65]	0.95* [0.01]	0.62** [0.01]	-0.15 [0.21]	0.63** [0.01]	0.09 [0.38]
Mean Promotions				9.17** [0.00]		9.87** [0.00]
Constant	-1.49* [0.01]	-5.26** [0.01]	-4.42** [0.00]	-2.07** [0.00]	-3.96** [0.00]	-2.40** [0.00]
Observations	5,295	8,275	16,486	16,486	16,486	16,486

Note: Robust p-values in brackets; robust standard errors are clustered by individuals; ** p<0.01, * p<0.05, + p<0.1. In Models 1 and 2, the models additionally include year and firm dummies. In Models 3 through 6, year dummies are used as exogenous variables in the first stage; firm dummies are additionally controlled for in all models in both stages. We removed individual-year observations with highest rank (rank of 11) from the analysis since they are not at risk of getting promoted from the current job.

APPENDIX

Figure A: Yearly Coefficients in the First Stage of Heckman Model

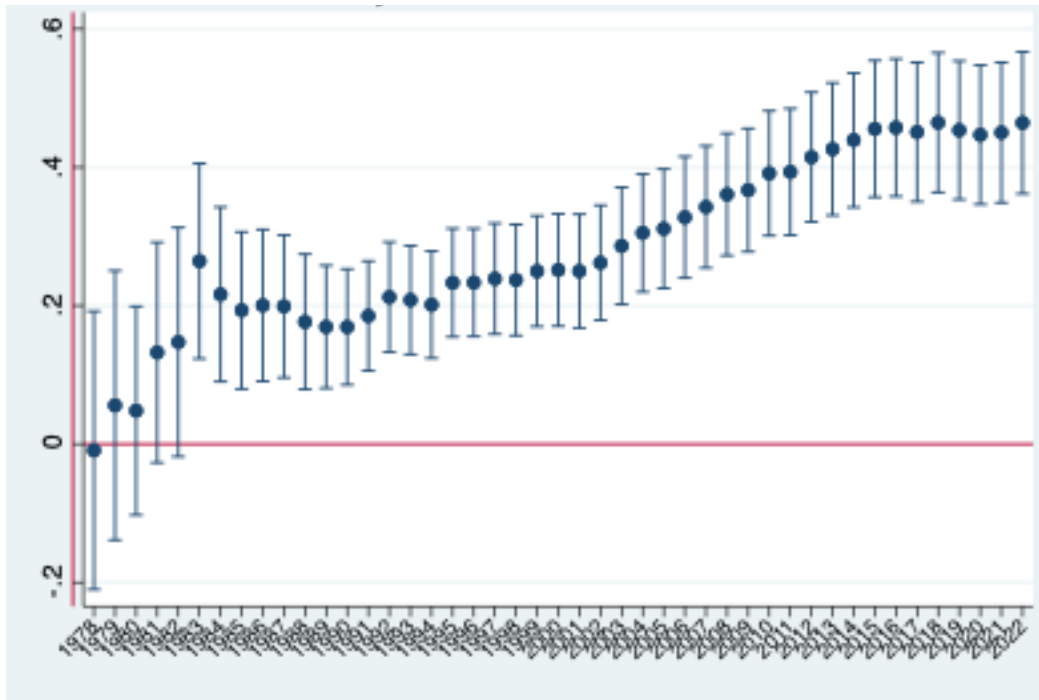


Table A: Determinants of productivity and collaborator diversity

	(1) Log number of patents	(2) Collaborator diversity
Specialization _{t-1}	0.15** [0.00]	
Log number of patents _{t-1}	0.93** [0.00]	
Specialization		-0.99** [0.00]
# of patents		0.04** [0.00]
Job tenure	0 [0.74]	0.00 [0.72]
Experience	-0.01** [0.00]	0.00 [0.86]
Experience squared	0.00** [0.00]	0.00 [0.55]
# of past employers	0.01 [0.30]	0.13* [0.04]
Female	0 [0.90]	-0.32* [0.03]
Rank	-0.01	0.00

	[0.31]	[0.86]
Constant	1.27**	1.27**
	[0.00]	[0.00]
Observations	5,248	17,287
R-squared	0.94	0.16

Note: P-values in brackets and robust standard errors are clustered by individuals, ** p<0.01, * p<0.05, + p<0.1; the model additionally controls for firm dummies and year dummies.

Table B: Spline analysis of the probability of promotion within scientific roles and patent counts

	(1)	(2)	(3)	(4)
	1	25%	50%	75%
Cutoff:		percentile	percentile	percentile
Specialization	0.62*	0.71*	0.64*	0.50+
	[0.03]	[0.02]	[0.03]	[0.05]
Job tenure	-0.02+	-0.02+	-0.03+	-0.03+
	[0.09]	[0.09]	[0.06]	[0.05]
Experience	-0.02	-0.02	-0.02	-0.02
	[0.46]	[0.44]	[0.42]	[0.46]
Experience squared	0	0	0	0
	[0.18]	[0.19]	[0.20]	[0.18]
# of patents <= cutoff	0.43*	0.25*	0.08*	0.03*
	[0.01]	[0.01]	[0.02]	[0.03]
# of patents > cutoff	0	0	-0.01	-0.01
	[0.70]	[0.56]	[0.28]	[0.16]
# of past employers	0.17**	0.17**	0.17**	0.17**
	[0.00]	[0.00]	[0.00]	[0.00]
Female	0.13	0.14	0.15	0.14
	[0.38]	[0.35]	[0.35]	[0.37]
Rank	-0.04	-0.04	-0.03	-0.04
	[0.54]	[0.56]	[0.59]	[0.59]
MBA	0.33	0.36	0.33	0.3
	[0.31]	[0.27]	[0.30]	[0.34]
Constant	-2.43**	-2.34**	-2.00**	-1.78**
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	6,366	6,366	6,366	6,366

Note: P-values in brackets and robust standard errors are clustered by individuals, ** p<0.01, * p<0.05, + p<0.1; Year dummies and firm dummies are additionally controlled in the model.

Table C: Spline analysis of the probability of promotion within managerial roles and patent counts

Cutoff:	(1)	(2)	(3)	(4)	(5)	(6)
	25% percentile		50% percentile		75% percentile	
	1 st stage: Transition to managerial role	2 nd stage: Managerial promotions	1 st stage: Transition to managerial role	2 nd stage: Managerial promotions	1 st stage: Transition to managerial role	2 nd stage: Managerial promotions
Specialization	0.37 [0.10]	-0.24 [0.13]	0.44+ [0.06]	-0.34* [0.04]	0.39+ [0.09]	-0.27 [0.11]
Rank	0.74** [0.00]	-0.08** [0.00]	0.74** [0.00]	-0.08** [0.00]	0.74** [0.00]	-0.08** [0.00]
Job tenure	-0.05** [0.00]	0.01 [0.42]	-0.05** [0.00]	0 [0.43]	-0.05** [0.00]	0 [0.44]
MBA	0.61** [0.01]	-0.14 [0.22]	0.62** [0.01]	-0.15 [0.20]	0.61** [0.01]	-0.14 [0.23]
Experience	0.02 [0.21]	0.05** [0.00]	0.02 [0.24]	0.05** [0.00]	0.02 [0.22]	0.05** [0.00]
Experience squared	0 [0.13]	-0.00** [0.00]	0 [0.15]	-0.00** [0.00]	0 [0.14]	-0.00** [0.00]
# of past employers	0.09+ [0.06]	0.03 [0.19]	0.09+ [0.06]	0.03 [0.21]	0.09+ [0.06]	0.03 [0.20]
# of patents <= cutoff	-0.14 [0.24]	0.11 [0.23]	0 [0.91]	-0.01 [0.66]	0 [0.79]	0 [0.52]
# of patents > cutoff	0.01 [0.15]	0 [0.74]	0.01 [0.21]	0 [0.54]	0.01 [0.15]	0 [0.95]
Female	-0.1 [0.48]	0.06 [0.41]	-0.09 [0.52]	0.05 [0.51]	-0.1 [0.48]	0.06 [0.43]
Mean Promotions		9.16** [0.00]		9.19** [0.00]		9.17** [0.00]
Constant	-4.01** [0.00]	-2.40** [0.00]	-4.41** [0.00]	-2.01** [0.00]	-4.36** [0.00]	-2.13** [0.00]
Observations	16,486	16,486	16,486	16,486	16,486	16,486

Note: P-values in brackets and robust standard errors are clustered by individuals, ** p<0.01, * p<0.05, + p<0.1; Year dummies are used as exogenous variables in the first stage; firm dummies are additionally controlled for in all models in both stages. We removed individual-year observations with highest rank (rank of 11) from the analysis since they are not at risk of getting promoted from the current job.

Table D: Estimation of promotions including collaborator network measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			<i>1st stage</i>	<i>2nd stage</i>			<i>1st stage</i>	<i>2nd stage</i>
	Promotion within scientific roles	Promotion to first managerial position	Transition to managerial role	Managerial promotions	Promotion within scientific roles	Promotion to first managerial position	Transition to managerial role	Managerial promotions
Specialization	0.68* [0.02]	1.02+ [0.05]	0.47* [0.03]	-0.26+ [0.08]	0.66* [0.02]	1.14* [0.04]	0.46* [0.04]	-0.24 [0.12]
Collaborator diversity	0.02 [0.37]	-0.04 [0.47]	0.02 [0.27]	0.03** [0.01]				
# of collaborators					0.00 [0.95]	0.01 [0.26]	0.00 [0.74]	0.004* [0.04]
Job tenure	-0.02 [0.18]	-7.58* [0.02]	-0.05** [0.00]	0.01 [0.37]	-0.02 [0.18]	-7.66* [0.02]	-0.05** [0.00]	0.00 [0.44]
Experience	-0.03 [0.27]	-0.03 [0.47]	0.02 [0.24]	0.05** [0.00]	-0.03 [0.24]	-0.03 [0.44]	0.02 [0.25]	0.05** [0.00]
Experience squared	0.00 [0.36]	0.00 [0.72]	0.00 [0.14]	-0.00** [0.00]	0.00 [0.38]	0.00 [0.82]	0.00 [0.15]	-0.00** [0.00]
# of past employers	0.20** [0.00]	0.06 [0.51]	0.09+ [0.06]	0.03 [0.21]	0.21** [0.00]	0.04 [0.66]	0.09+ [0.06]	0.03 [0.24]
# of patents	0.00 [0.54]	0.02+ [0.08]	0.00 [0.27]	0.00 [0.86]	0.00 [0.75]	0.01 [0.40]	0.01 [0.33]	0.00 [0.47]
Female	0.14 [0.39]	0.16 [0.56]	-0.09 [0.53]	0.06 [0.38]	0.13 [0.45]	0.19 [0.49]	-0.09 [0.52]	0.07 [0.34]
Rank	-0.06 [0.38]	2.68** [0.00]	0.74** [0.00]	-0.08** [0.00]	-0.06 [0.41]	2.69** [0.00]	0.74** [0.00]	-0.07** [0.00]
MBA	0.16 [0.66]	0.95* [0.02]	0.61** [0.01]	-0.15 [0.22]	0.16 [0.65]	0.95* [0.02]	0.61** [0.01]	-0.14 [0.24]
Mean promotion				9.35** [0.00]				9.21** [0.00]
Constant	-1.53** [0.01]	-5.16** [0.01]	-4.47** [0.00]	-2.16** [0.00]	-1.49* [0.01]	-5.49** [0.01]	-4.43** [0.00]	-2.15** [0.00]
Observations	5,295	8,275	16,486	16,486	5,295	8,275	16,486	16,486

Note: P-values in brackets and robust standard errors are clustered by individuals, ** p<0.01, * p<0.05, + p<0.1; For Models 3 and 4, year dummies are used as exogenous variables in the first stage; firm dummies are additionally controlled for in all models in both stages. We removed individual-year observations with highest rank (rank of 11) from the analysis since they are not at risk of getting promoted from the current job.

Section 1: Using generative AI to construct the career ladder using job postings

- A. Data collection on job postings: We aimed to collect at least 20 postings per rank. We organized the job postings by date and started collecting job postings as they occurred within the Indeed sample. The proportion of postings in our sample is thus representative of the proportion as they occur. We stopped when we had at least 20 observations for each rank (ranks 1-8). We were unable to find enough postings for scientific roles in rank 4 so these were not included in this analysis. We found that there were far more Associate Director and Director job postings than any other position – there were approximately twice the number of these positions than that for a Principal Scientist. Of the relevant job postings on the Indeed platform, we were able to find only 20 positions that had Vice President in the job title, and only 2 that had Senior Vice President in the title. This is not unexpected as firms often use headhunters for these positions and do not advertise for these positions publicly.
- B. Analysis
- a. Analysis based on tasks
 - i. We asked ChatGPT to generate a list of phrases signifying the tasks that it associates with scientific jobs within pharmaceutical firms. This method relied on ChatGPT’s natural language processing capabilities and ability to infer. Two coauthors then verified whether this list was accurate or not. We found all the tasks that ChatGPT listed to be accurate and comprehensive, but we made one modification and asked it not to consider Supply Chain management as a scientific or managerial task. We did the same for managerial tasks and found the list generated by ChatGPT to be reasonable.
 - ii. We then generated a prompt and asked ChatGPT to classify the job postings into scientific and managerial components by calculating the total number of tasks listed within the posting and calculating the proportion of tasks that were scientific vs. managerial. We engineered this prompt first through the interactive mode to ascertain its reliability and replicability. That is, we first fed ChatGPT 10 job descriptions interactively, and once we ascertained that it was doing the categorization correctly and reliably, we automated the process. The final prompt that we used is included in Section 1 (Part A) of the Appendix.
 - b. Analysis based on keywords
 - i. We first asked ChatGPT to generate a list of keywords associated with scientific jobs within pharmaceutical firms and followed up with a manual perusal by the entire coauthor team. We found all of the keywords that ChatGPT listed to be accurate and comprehensive. We did the same for managerial keywords and repeated the manual examination by the coauthor team to ascertain whether they were accurate.
 - ii. We then generated a prompt and asked ChatGPT to classify the job postings into scientific and managerial components by calculating the total number of keywords listed within each posting and calculating the proportion of keywords that were scientific vs. managerial. The prompt that we used has been included in Section 1 (Part B) of the Appendix.

Table J: Job Postings Analyzed

Job Title	Rank	No. of Job Postings
Scientist/Research Scientist	1	32
Senior Scientist/Senior Research Scientist	2	27

Principal Scientist/Fellow	3	25
Manager/Associate Director	4	45
Director	5	46
Senior Director	6	24
Executive Director	7	31
Vice President	8	20
Senior Vice President	9	2

Part A: Inferencing from tasks listed in job descriptions

ChatGPT prompt:

I will ask you to categorize job postings advertised by pharmaceutical firms. From these postings I will ask you to rate each by how much the job is for a scientific role and how much is for a managerial role. To do this task you should focus on the job responsibility. Identify the tasks and then analyze how many of the tasks are strictly scientific and how many are strictly managerial. If the task entails leading it should be strictly managerial. If the task is about communication then it should not be counted as managerial or scientific since it falls under both. If the task is about coordination it is managerial.

To perform this task,

Step 1: Identify the phrases or keywords associated with a scientific role vs. managerial role. Domain or area specific words such as biotechnology, immunology etc. should not be considered managerial or scientific. Tasks to do with collaboration should not be counted as managerial. If the job description specifies teamwork then that should not be counted as managerial.

Step 2: Identify a unique list of responsibilities from the job posting. Only focus on the text that is about the responsibility of the person who will perform this job. Provide direct quotes from the job posting.

Step 3: categorize each responsibility as scientific or managerial, based on keywords and phrases that match the above categories from Step 1.

Step 4: count the number of responsibilities with scientific vs. managerial component respectively.

Step 5: generate a proportion of keywords for each component.

Now, I want you to populate the proportion of scientific vs. managerial component in a spreadsheet. I have uploaded an excel file where there are job postings. Can you put the % of scientific component in column H and managerial component in column I?

ChatGPT output: Tasks associated with scientific and managerial activities within pharmaceutical firms

Scientific Tasks

- **Research & Development:**
 - Conduct experiments
 - Analyze data
 - Develop hypotheses
 - Write scientific reports
 - Publish research findings
 - Perform laboratory work
 - Test formulations
 - Develop protocols
- **Technical Skills:**
 - Use of scientific equipment (e.g., spectrometers, chromatography systems)
 - Expertise in biostatistics
 - Bioinformatics analysis

- Genomic sequencing
- Chemical synthesis
- Clinical trial design
- **Specialized Knowledge:**
 - Pharmacokinetics
 - Pharmacodynamics
 - Toxicology assessments
 - Molecular biology
 - Cell culture techniques
 - Biotechnology processes

Managerial Tasks

- **Leadership:**
 - Lead a team
 - Mentor junior staff
 - Strategic planning
 - Set project goals and timelines
- **Coordination:**
 - Manage cross-functional teams
 - Coordinate project activities
 - Resource allocation
 - Budget management
 - Ensure compliance with regulations
- **Communication:**
 - Present findings to stakeholders
 - Liaise with external partners
 - Prepare project updates
 - Develop and maintain collaborative relationships

To demonstrate how we can analyze a job posting, here's a hypothetical example of responsibilities and their categorization:

1. Lead a team of researchers in developing new drug formulations.
 - **Managerial** (lead a team)
2. Conduct in vitro and in vivo experiments to test drug efficacy.
 - **Scientific** (conduct experiments)
3. Coordinate with the regulatory affairs department to ensure compliance with FDA regulations.
 - **Managerial** (coordinate with regulatory affairs)
4. Present research findings at scientific conferences.
 - **Communication** (present findings)
5. Mentor junior scientists in laboratory techniques and data analysis.
 - **Managerial** (mentor junior staff)
6. Analyze data from clinical trials using biostatistical methods.
 - **Scientific** (analyze data)

Part B: Calculating managerial and scientific keywords from job descriptions

ChatGPT output: Keywords associated with scientific and managerial activities within pharmaceutical firms

ChatGPT prompt:

You will examine job postings advertised by pharmaceutical firms. I have provided a spreadsheet with 252 job postings in column G. For each posting, rate how much the job has a scientific component vs. managerial component.

To perform this task,

Step 1: identify the phrases or keywords associated with a scientific role vs. managerial role.

Step 2: identify texts that is about the responsibility of the person who will perform this job.

Step 3: Using the text identified in Step 2 and using keywords from Step 1, generate the number of exact matches found in the document for scientific role vs. managerial role. Put the number of matches in column H (scientific) and column I (managerial)

Step 4: generate a proportion of keywords for each component.

Step 5: put the % of scientific component in column J and managerial component in column K

Step 6: Return the spreadsheet with the added columns in Step 5.

Step 7: produce a scatter plot of % managerial and rank (column E)

ChatGPT output:

Scientific Keywords	Managerial Keywords
• Research	• Manage
• Experiment	• Supervise
• Analysis	• Oversee
• Data	• Strategy
• Laboratory	• Direct
• Scientific	• Coordinate
• Technique	• Leadership
• Protocol	• Budget
• Discover	• Administer
• Develop	• Mentor
• Clinical	
• Biological	
• Chemical	
• Pharmaceutical	
• Technical	

Figure 1A: Box Plot of Rank vs. Proportion of managerial keywords

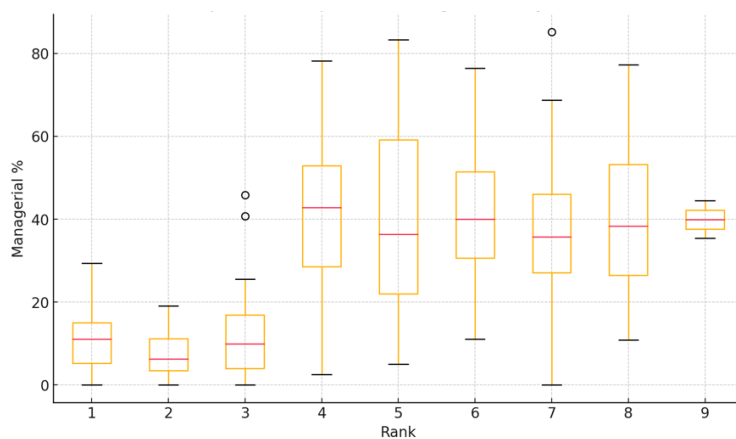
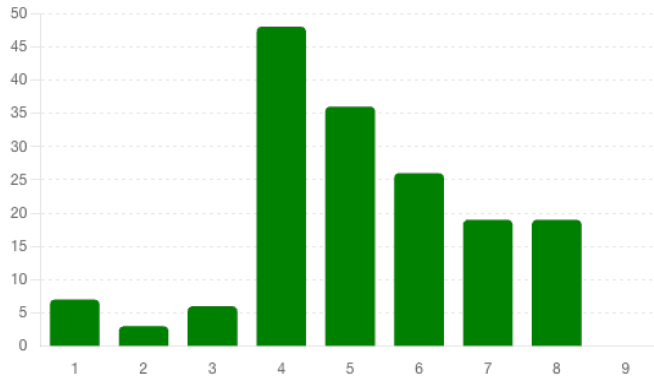
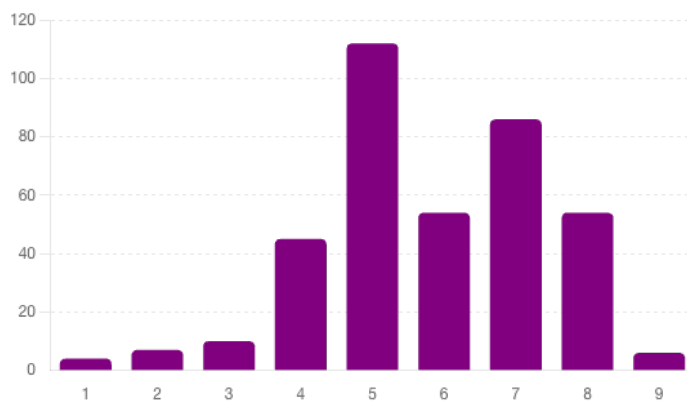


Figure 1B: Frequency of the occurrence of the word “manage” within job postings by Rank



Note: The x-axis represents the rank and the y-axis represents the frequency of occurrence of the word “manage.”

Figure 1C: Frequency of the occurrence of the word “strategy” within job postings by Rank



Note: The x-axis represents the rank and the y-axis represents the frequency of occurrence of the word “strategy.”

Section 2. Patenting behaviors across the career ladder

We theorized and demonstrated the dilemma created by the interplay of durable skills and dynamic job demands for individuals over the course of their careers, focusing on its implications for how people get promoted. In a supplementary analysis, we shifted our focus to how people acquire different experiences, examining whether scientists alter the patterns of skills that they acquire in response to the changing demands of the job. Specifically, we assessed whether people have a greater propensity to diversify into new areas once they are in managerial roles by predicting the likelihood of applying for a patent in a new patent class.

We created a variable *Patent in new class*, which was coded as 1 if the patent is within a patent class different from all other previously applied patents (up to patent_{n-1}) and 0 otherwise. We used a linear probability model to predict the likelihood of applying for a patent in a new class at the individual-patent level.²² In this analysis, we additionally controlled for the share of patents in each class up to patent_{n-1} to account for the possibility that certain patent areas are more conducive to patenting within or across patent classes. We further controlled for whether the individual had only ever applied to a single patent class prior to the focal patent, as exploratory analyses had shown that scientists with just one patent class were particularly likely to add another class.

Results are reported in Table K below. Contrary to our expectations, Model 1 does not show a

²² We were able to replicate our results using a logit regression model; we present the linear probability model in this paper for ease of interpretation.

strong correlation between occupying a managerial position and the likelihood of patenting in a new class. Although our main findings suggest that managers benefit from building a broader skills portfolio, we find little evidence that managers are more likely to diversify their patent portfolio once they enter managerial ranks. It is possible that the constraints of the managerial role make it more challenging for managers to branch out into new knowledge fields.

In Model 2, we added the interaction between managerial position and the level of specialization at the time of managerial promotion. We find a significant interaction ($\beta=0.08$; $p=0.05$). This indicates that people are more likely to diversify in managerial positions if they were previously more specialized, suggesting an increased effort to adapt. Once we control for this interaction, we find a negative main effect of whether they hold a managerial position, indicating that those who already have a very low level of specialization become *less* likely to add new patent classes as they reach managerial ranks, while those who are more specialized do broaden their portfolios. This finding is unlikely to result from a mechanical limitation—where individuals with a diversified portfolio have fewer new patent classes available to expand to—given the extensive range of patent classes ($n=129$) and the fact that individuals in our sample on average patent across three classes throughout their careers. One interpretation of these results is that managers have fewer opportunities to diversify research areas as they climb up the ranks, but that those with the most need to diversify – those who have the narrowest prior experience – still attempt to do so to meet the greater need for breadth in managerial roles.

Table K: Estimation of patenting in new class using linear probability model

	(1) Patenting in new class	(2) Patenting in new class
Managerial position	-0.01 [0.13]	-0.06** [0.01]
Specialization (up to previous patent)	0.02 [0.47]	-0.01 [0.74]
Specialization x Managerial position		0.08* [0.05]
Patented in only one class (up to previous patent)	0.20** [0.00]	0.21** [0.00]
Number of patent classes (up to previous patent)	0.00 [0.67]	0.00 [0.65]
Rank	0.00 [0.12]	0.00+ [0.10]
Job tenure	-0.00* [0.03]	0.00 [0.66]
# of past employers	0.00 [0.20]	0.00 [0.69]
Female	0.01 [0.41]	0.01 [0.37]
Experience	0.00 [0.36]	0.00 [0.44]
Experience squared	0.00 [0.55]	0.00 [0.64]
MBA	0.00 [0.94]	0.00 [0.91]
Constant	0.05*	0.06*

	[0.03]	[0.02]
Observations	10,833	10,833
R-squared	0.12	0.12

Note: Robust p-values in brackets and robust standard errors are clustered by individuals, ** p<0.01, * p<0.05, + p<0.1; firm dummies and share of patents in each patent class are additionally controlled for in all models. These results are replicated using logit regression model.

Section 3. Survey experiment

Exhibit 1. An example of a profile pair displayed for survey participants

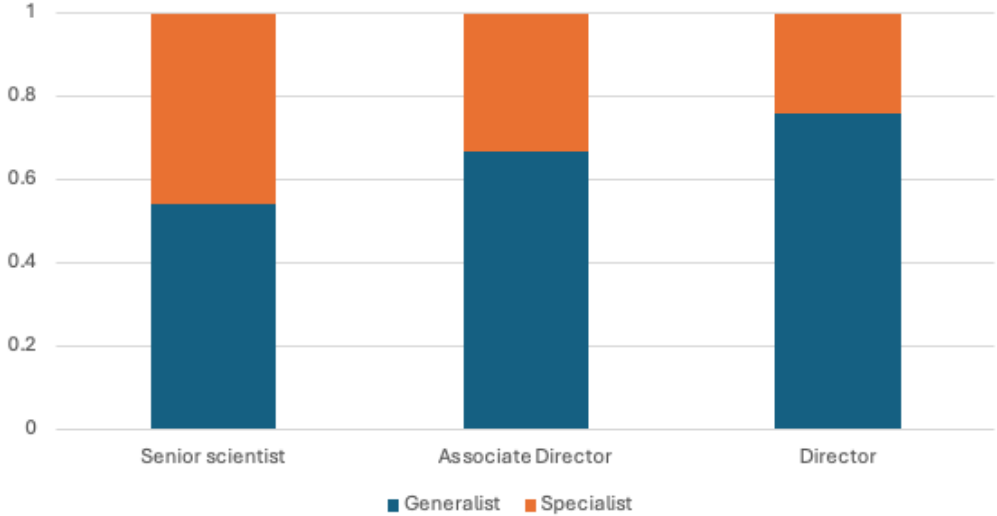
For the Director position, we are considering two candidates, both of whom are Associate Directors in the Oncology Department at BioInfo.

A Director will set strategic direction for research or development programs, leads teams, and aligns scientific goals with organizational priorities and regulatory expectations.

Name: Candidate A Level of Education: Ph.D. Work Experience: BioInfo (2018 - Present)		Name: Candidate B Level of Education: Ph.D. Work Experience: BioInfo (2018- Present)	
Area	Completed projects	Area	Completed projects
Lung cancer	USPTO 695003 "Bispecific Antibodies Targeting ALK and PD-L1 in Lung Cancer" USPTO 700232 "Smart Inhalers for Targeted Aerosol Delivery of Immunomodulators" USPTO 710523 "Circulating Tumor DNA Detection Panels for Monitoring EGFR Mutations" USPTO 710525 "Autologous T-cell Expansion Platforms for Lung Cancer Immunotherapy" USPTO 710527 "Synthetic Exosome Mimetics for KRAS Mutant NSCLC Treatment" USPTO 710533 "High-Throughput Screening of Lung Tumor Organoids for Personalized Therapy"	Blood cancer USPTO 695001 "Small Molecule Inhibitors of JAK-STAT Signaling in Lymphoma" USPTO 695022 "Diagnostic Biomarkers for Early Detection of Acute Lymphoblastic Leukemia"	Skin cancer USPTO 700221 "Combinatorial Vaccine Approaches for UV-Induced Skin Tumors" USPTO 700226 "CRISPR-Based Therapeutics for Melanocyte Transformation Suppression"
		Bladder cancer	USPTO 710234 " Synthetic Peptides for Immune Activation in Urothelial Carcinomas" USPTO 710325 "Biodegradable Hydrogel Carriers for Sustained Drug Release in Bladder Wall"

	USPTO 710535 "Biomaterial Scaffolds for In Vivo Modeling of Lung Tumor Progression"	Lung cancer	USPTO 710327 " DNA Methylation Signatures for Early NSCLC Detection in Sputum Samples"
	Total: 7 projects		Total: 7 projects

Figure 3A: Proportion of participants choosing a generalist vs. specialist for a given role



BIOGRAPHICAL SKETCHES

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Shinjae Won (wons@ewha.ac.kr) is an Associate Professor of Management at the Ewha School of Business, Ewha Womans University. She received her PhD in Management from the Wharton School of the University of Pennsylvania. Her research examines how firms acquire, retain, and reallocate human capital, as well as what enables individuals to make desirable moves within and across organizations.

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