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Cascading innovation: R&D team design and performance implications of mobility

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Abstract

Research Summary: Given the high cost of external hiring and uncertainty related to performance benefits, how can organizations foster an environment that maximizes the post-mobility performance of external hires and their collaborators? In this article, I posit that R&D team design is an important factor that could shape the post-mobility performances of both groups. Building on the interfirm mobility, innovation, and teams literatures, I argue that technological knowledge diversity within teams and across teams could differently impact innovation performance. Analyzing 63,976 interfirm moves of engineers and scientists, I find that the post-mobility performances of external hires and teammates are conditioned by team design. A high level of within-team diversity improves the performances of both groups, while a high level of across-team diversity hurts their innovation outcomes.

Managerial Summary: In the war for talent, firms often offer premium wages to source external hires. Yet there have been unclear expectations about the post-mobility outcomes of these hires and the implications for team performance. To better assess the value of hiring, managers should look beyond the performance of external hires and also consider team member performance. In the context of knowledge production activities, external hires, on average, experience an improvement in innovation performance after they move. Working with an external hire reduces the productivity of immediate collaborators but leads to more breakthrough innovations with greater technological impact. Most importantly, the performances of external hires and their teammates can be further improved by effectively designing R&D teams. Recomposing teams such that a high level of diversity exists within a team but minimal divergence across teams creates an environment that appears to enhance post-mobility innovation activities.

KEYWORDS

innovation, knowledge management, knowledge spillovers, labor mobility, R&D team design

1 | INTRODUCTION

Interfirm mobility by engineers and scientists is an important and common channel for sourcing and transferring knowledge across firms (Almeida & Kogut, 1999; Arrow, 1962; Singh & Agrawal, 2011; Song, Almeida, & Wu, 2003). In technology-intensive industries, job hopping among patent inventors is prevalent; in the United States, at least 44% of all patent inventors change firms at least once, with the average inventor working for 2.5 firms.[1] While the large body of work on mobility and knowledge spillover highlights how an external hire brings a competitive advantage to a firm, research on interfirm mobility and human capital suggests that hiring talent externally also carries significant costs. External hires, who often perform worse after the move, are paid significantly more than incumbent employees (Bidwell, 2011). Organizations incur further costs searching for and then onboarding the best and brightest talent (Glebbeek & Bax, 2004; Shaw, Duffy, Johnson, & Lockhart, 2005). Thus, whether firms realize the desired knowledge production benefits from new hires and how to maximize gains from hiring are key strategic concerns.

Further complicating the assessment of the value of external hiring, we know relatively little about the performance of teammates who collaborate with external hires. Scholars have studied "learning-by-hiring" by examining how much destination firms *exploit* or cite the inventions previously produced by the recruit or the source firm (Corredoira & Rosenkopf, 2010; Palomeras & Melero, 2010; Rosenkopf & Almeida, 2003; Song et al., 2003).[2] Yet we have still have much to learn about how the new hire contributes to firm performance through *future collaborative knowledge production*—specifically, whether the teammates become more productive

[1]Calculated by the author based on U.S. patent data from 1975 to 2017. The sample includes movements between U.S. companies and corporations. These figures are most likely underestimates, given that an employee needs to apply for a patent to be included in the sample.

[2]For example, Singh and Agrawal (2011) find evidence that hiring firms double the use of the recruit's prior inventions, and that nearly half of the boost in the use of the recruit's past patents is driven by citations by the recruit and their teammates. While helpful in understanding the motivation behind external hiring, citing the hire's prior work does not necessarily mean that firm members have absorbed the new knowledge and improved their innovative capacities.

and generate better quality inventions at their firms after working with the external hire—as well as how to successfully integrate new hires into teams. Incidentally, Mawdsley and Somaya (2016) have called for more research that both untangles the processes behind learning-by-hiring and investigates strategies for integrating these hires.

Given the high costs of hiring and uncertainty related to the performance contributions of external hires and their teammates, what are the conditions under which firms can maximize the post-mobility innovation performances of both groups? Simply adding talent to the mix does not necessarily guarantee the successful acquisition and utilization of human capital (Groysberg, Lee, & Nanda, 2008). In this article, I posit that effectively designing R&D teams is an important yet less explored integration strategy. The collaborative production of knowledge is a critical source of innovation in technology-intensive industries (Choudhury & Haas, 2018; Singh & Fleming, 2010; Teodoridis, 2018; Wuchty, Jones, & Uzzi, 2007). Different ways of structuring teams can shape the knowledge production outcomes of both external hires and their teammates.

In particular, I focus on two firm-level team design factors related to "technological knowledge diversity" (henceforth referred to as "knowledge diversity" and "technological diversity"): *within-team diversity* captures whether members of a particular team have similar technological knowledge backgrounds, while *across-team diversity* measures whether teams share more or less diverse sets of technological knowledge with respect to other teams in the firm. Drawing on the organizational learning and interfirm mobility literatures, I posit that high within-team diversity offers more collaboration benefits than costs to teams, while high across-team diversity hinders the innovation process. Further, I investigate the effect of dyadic relations between external hires and other team members—namely, *dyadic knowledge distance*—on the innovation performances of both groups.

Using U.S. patent data on a sample of 63,976 mobility events by patent inventors across different industries, I find that the performances of hires and team members are conditioned by team design: a high level of within-team diversity and a low level of across-team diversity are associated with improvement in innovation performance for both external hires and their teammates. Further, assigning new hires to teams with members who have more distant knowledge bases mitigates the productivity decline.

This study contributes to research at the nexus of interfirm mobility, innovation, and organization design. Specifically, this article highlights how the structure of knowledge within firms could magnify or reduce performance benefits from external hiring. By considering diversity across different teams within a firm, I demonstrate the importance of considering the knowledge structure that lies outside of one's team boundary. Distinguishing the performance contribution of external hires and the performance ramifications for their teammates allows us to better understand the process behind learning-by-hiring. These findings have important implications for managers at innovation-driven firms. Most importantly, firms can foster innovation by increasing the diversity of knowledge and experience within teams. But external hires and their teammates do not reap the benefits from a broad set of knowledge across teams.

2 | INTERFIRM MOBILITY AND INNOVATION

2.1 | Innovation performance of external hires and team members

To better understand how R&D team design shapes the post-mobility performances of external hires and their teammates, I first discuss mechanisms related to how mobility shapes performances of external hires and their teammates. These mechanisms serve as the theoretical underpinnings of my hypotheses on team knowledge diversity.

Research on interfirm mobility provides inconsistent findings related to post-mobility performance of external hires. On the one hand, two mechanisms lead to a decline in an external hire's performance after mobility: adjustment and coordination costs. First, external hires suffer from high adjustment costs due to the limited utilization of firm-specific human capital accumulated from the prior firm (Bidwell, 2011; Groysberg et al., 2008; Mayer, Somaya, & Williamson, 2012; Raffiee & Byun, 2020). Firm-specific human capital—such as routines, procedures, and interpersonal relationships developed at the prior firm—is not easily transferable and needs to be redeveloped at the new firm. Second, external hires incur high team-level coordination costs when working with new colleagues at the hiring firm. A loss of team-specific or colleague-specific human capital could lead to a decline in productivity (Campbell, Saxton, & Banerjee, 2014; Ethiraj & Garg, 2012; Jaravel, Petkova, & Bell, 2018). Every team requires coordination among individuals with specialized knowledge (Rico, Sánchez-Manzanares, Gil, & Gibson, 2008), and such coordination could be more difficult among members who share fewer similarities in knowledge, routines, and relational capital.

On the other hand, external hires may benefit from new and complementary resources not present at the departure firm (Hoisl, 2007). The new knowledge available to hires, if used with existing knowledge and processes, can create new combinations of outputs. In addition to the knowledge benefits, recent research highlights the conditions under which the costs of mobility could be minimized. When human capital is highly transferable and applicable to a new organization, any disruption in firm-specific human capital may be offset by knowledge benefits. For instance, Tartari, Di Lorenzo, and Campbell (2020) show that the skills and knowledge in academia are portable and less organization-specific, thus be easily utilized after moving.

Although the performance consequences of external hires have been explored in other contexts, it is unclear whether the mobility would bring advantages or disadvantages to teammates, who collaborate with external hires at the firm. On the one hand, external hires could bring advantages to their teams, not only through the exploitation of prior knowledge (Singh, 2005), but also through successful exploration activities, like developing new competencies and recombinations of existing and new ideas, for two reasons. First, teammates working with an external hire are more likely to be exposed to a new, complementary stock of technological knowledge from the external hire's source firm (Agarwal, Ganco, & Ziedonis, 2009; Agrawal, Cockburn, & McHale, 2006; Jaffe, Trajtenberg, & Henderson, 1993; Marx, Strumsky, & Fleming, 2009; Samila & Sorenson, 2011; Tzabbar, Aharonson, & Amburgey, 2013). Compared to existing employees, external hires are more likely to bring in complementary human capital, addressing knowledge gaps in the team or at the firm. Second, new hires can also catalyze team member learning. While incumbent teammates tend to limit themselves to local searches given less motivation to seek, acquire, and absorb information from others (Stuart & Podolny, 1996; Tzabbar, 2009), external hires may prompt exploratory searches by teammates, as well as bring social capital, such as ties from their prior firm (Raffiee & Byun, 2020). This expanded network of information and knowledge sources can provide ongoing channels for learning and knowledge spillovers (Reagans & McEvily, 2003; Singh, 2005).

On the other hand, collaborating with external hires may raise coordination costs, compared to working with incumbent employees. Incumbent team members may need to assist the external hire with training and onboarding (Rollag, Parise, & Cross, 2005). These coordination difficulties likely increase when teammates work with external hires who possess more distant knowledge with little overlapping experience and few shared routines (Montoya-Weiss, Massey, & Song, 2001; Weber & Camerer, 2003).

In sum, there exist both benefit (i.e., complementary knowledge assets, learning) and cost (i.e., adjustment costs, coordination costs) mechanisms related to post-mobility performance of external hires and their team members. I next describe how individual performance may depend on the organizational structure. Specifically, I hypothesize how these mechanisms would be affected by the organization of knowledge within and across teams.

2.2 | The role of R&D team design on innovation performance

2.2.1 | Team knowledge diversity

Given the increasing dominance of teams in the production of knowledge (Wuchty et al., 2007) and that teams are more likely to produce "breakthroughs" than solo inventors (Singh & Fleming, 2010), it is important to consider how collaborative teams are structured. Team structures determine how employees access, share, and integrate new knowledge (Edmondson & Harvey, 2018; Mortensen & Haas, 2018). Examining the role of team design in the performance of new hires, as well as their teammates, can offer new insights to managers on how to maximize the gains from external hiring.

With a stock of employees who each possesses different knowledge accumulated throughout their careers, managers have discretion in organizing the *knowledge diversity* within firms.[3] There are two distinct approaches to organizing knowledge diversity into teams within a firm: the diversity of individuals' technological experience can be distributed (a) within a team ("within-team diversity") and (b) between teams in a firm ("across-team diversity"). Figure 1 illustrates a hypothetical example of how knowledge diversity can be organized within a firm. The same set of individuals can be organized into teams with different levels of high or low within-team diversity and across-team diversity. Whether a firm has high versus low knowledge diversity is a function of the numbers of individuals, teams, unique technological fields, and, most importantly, the organization of individuals within and across teams.

Prior investigations into R&D team design have examined several dimensions of diversity (e.g., demographics, task experience, organizational affiliations) *within* teams (Choudhury & Haas, 2018; Hoisl, Gruber, & Conti, 2017; Reagans & Zuckerman, 2001). Yet considering the level of knowledge diversity *across* teams is equally important when considering the stock of knowledge that exists at a firm (Aggarwal, Hsu, & Wu, 2020; Hansen, 2002).[4] Firms commonly

[3]In this article, I remain agnostic about how teams are formed within a firm. The creation and management of teams vary across companies and industries. Companies like Hewlett-Packard and Motorola are known for allowing teams to form "organically" (Katzenbach & Smith, 1993), while biotech and academia are examples of fields pushing for agile, self-forming, and self-organized teams (Di Fiore, West, & Segnalini, 2019). On the flip side, many firms design teams around relevant scientific domains or strategic initiatives. Regardless of how teams are formed, managers at firms have discretion over designing teams or, at a minimum, guiding employees on how best to form and function within teams.

[4]Aggarwal et al. (2020) explore how firms with diffuse structures (high within-team and low across-team diversity) and concentrated structures (low within-team and high across-team diversity) affect firm-level innovation quality. These researchers find a positive association between concentrated structures and firm performance. Yet their paper addresses a different question with distinct insights. First, the researchers capture all measures at the firm level, while I examine an individual's change in performance following a mobility event. I attempt to tackle endogeneity concerns, such as (a) the presence of an omitted firm-level variable (e.g., superior management team, acquisitions) that could be associated with both team structure and innovation performance and (b) reverse causality. Second, they describe

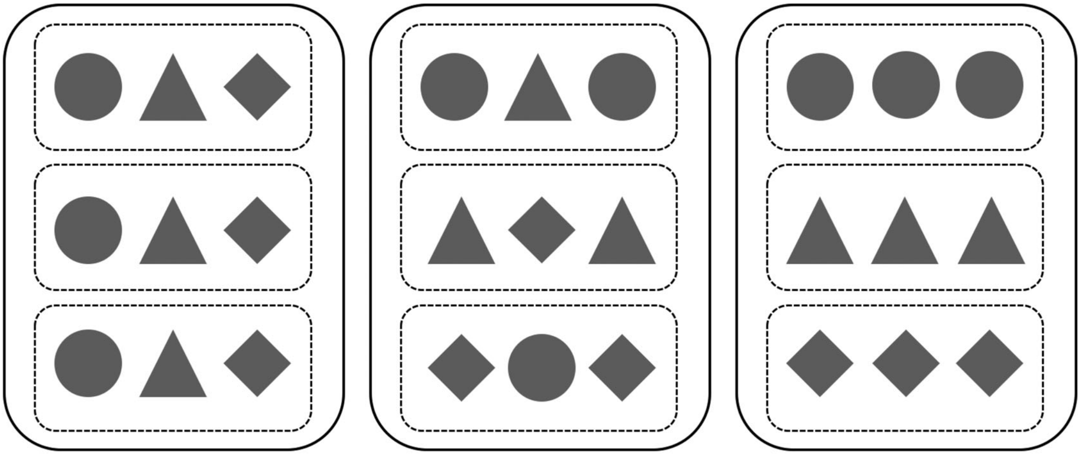

FIGURE 1 Within-team diversity and across-team diversity. The solid lines represent firm boundaries and dashed lines represent team boundaries. Each inventor possesses knowledge in one of the three fields: circle, triangle, and rhombus. If the inventors are assigned to three teams of three, the teams can be organized in at least three different ways. Firm A has high within-team diversity and low across-team diversity. Firm C has low within-team diversity and high across-team diversity. Firm B has an intermediate level of within-team and across-team diversity. Here, the two diversity measures may appear inversely related, since each team has the same number of inventors with the same set of knowledge. Empirically, however, the relationship between the firm-level average within-team and across-team diversity measures is not necessarily dependent or correlated.

encourage employees to build relationships outside their immediate teams in order to share ideas and discover new collaboration opportunities. For example, Apple's new "spaceship" campus has been lauded for promoting collaboration activities across units. The doughnut-shaped building allows employees to easily access members on the opposite side of the ring through both the inner and outer perimeters. Rather than being stable and rigidly bounded, in recent years, teams have become more "fluid, overlapping, and dispersed" with blurrier boundaries (Mortensen & Haas, 2018). Thus, the knowledge an employee is exposed to and the extent of knowledge sharing at an organization are also dependent on the diversity of knowledge residing across different teams.

2.2.2 | Within-team diversity

The diversity of knowledge and experience within teams could affect the benefits and costs associated with post-mobility performance—specifically, complementary knowledge, learning,

within-team diversity and across-team diversity as mutually exclusive relationships, while I describe the two constructs as not necessarily dependent or correlated (as shown in Figure 2). In addition, these researchers focus on the biotechnology sector, with a relatively limited scope of technological classes compared to other sectors (e.g., electronics). In my paper, I examine the effects across many different industries with varying firm sizes and scope. The present paper has implications not only for the R&D team design literature but also for careers and human capital management research.

adjustment costs, and coordination costs. Firms with a higher level of within-team diversity offer two benefits: greater complementary knowledge assets and more learning opportunities. First, external hires and teammates from diverse teams are more likely to possess knowledge assets that could complement each other's existing knowledge and skills. To derive novel combinations of previously disparate technological domains, different and diverse knowledge must be both present and accessible (Fleming, 2001; Weitzman, 1998). Thus, the knowledge benefit mechanism is likely to be stronger with a greater chance of developing new competencies and more creative recombination opportunities within a team (Cohen & Levinthal, 1989; Makri, Hitt, & Lane, 2010; Singh & Fleming, 2010; Taylor & Greve, 2006). Second, a wider set of knowledge and skills could enhance members' learning capabilities—such as finding a novel solution, providing greater knowledge recombination opportunities, and avoiding groupthink (Gruber, Harhoff, & Hoisl, 2013; Singh & Fleming, 2010; Taylor & Greve, 2006). Additional learning benefits accrue as members of diverse teams have broader social networks with indirect ties to other groups (Reagans & Zuckerman, 2001), thus enhancing the likelihood of creative and efficient technological solutions.

In terms of costs, members at firms with higher average within-team diversity could experience greater difficulty coordinating collaboration activities and integrating each other's knowledge inputs. As teams require coordination (e.g., common language, standardized routines), such challenges could increase with members who possess more distant knowledge and fewer similarities in experiences and routines. However, past research has shown that coordination conflict, which is a common challenge for all teams regardless of whether or not they share similar or diverse knowledge bases, can be minimized if they have an efficient division of labor and specialization (Ethiraj & Garg, 2012). Members of a team characterized by specialized knowledge can each focus on the relevant parts of the tasks or products. This specialized, collaborative work enables each member to develop expertise (Reagans, Miron-Spektor, & Argote, 2016). Furthermore, individuals at firms with higher overall within-team diversity—those with more experience interacting with people with various knowledge backgrounds on average—will be better equipped to coordinate with new hires than those who have worked with similar others. Thus, the mutual adjustment and synchronization process among team members could be smoother at firms with greater within-team diversity.

Scholars have tested the positive effect of within-team diversity by exploring various sources of diversity and different organizational outcomes, such as the effect of formal and informal organization unit membership diversity on patent scope and speed (Choudhury & Haas, 2018); the effect of job-related experience diversity and team efficiency (Hoisl et al., 2017); and the effect of demographic and network diversity on team productivity (Reagans, Zuckerman, & McEvily, 2004). Although these studies consistently show that having a high level of diversity within a team is beneficial, I revisit this hypothesis for three reasons. First, the effect of within-team diversity based on technological knowledge experience of employees has not been tested with regard to their innovation performance. As I detail in Section 3, I test the effect of within-team diversity on various innovation performance measures, including productivity, impact and creativity of inventions, and learning. Second, the effect of within-team knowledge diversity has not been compared and contrasted with the effect of diversity across different teams. In the next section, I explain why the benefits of knowledge diversity are not realized if the locus of knowledge resides outside of the focal employee's team. Finally, within-team diversity has not been tested with respect to external hires and team members. The effects of within-team diversity on external hires could have a different direction or magnitude compared to the effect on the average incumbent employee at the firm. External hires, who have a more distant knowledge base than the average firm employee, may benefit more from greater complementarity of assets and learning. Alternatively, they may also incur greater costs with greater diversity, as adjustment costs and coordination costs for more new team members. Thus, I examine the relative effects of within-team diversity on external hires and their teammates separately.

Hypothesis (H1a). *External hires who move to firms with higher levels of within-team knowledge diversity will, on average, experience higher innovation performance compared to those who move to firms with lower levels of within-team knowledge diversity.*

Hypothesis (H1b). *Teammates at firms with higher levels of within-team knowledge diversity will, on average, experience higher innovation performance compared to those at firms with lower levels of within-team knowledge diversity.*

2.2.3 | Across-team diversity

Considering knowledge diversity as existing only within a bounded team does not fully capture the learning channels that may exist at an organization. Across-team diversity captures overall knowledge diversity across members in a firm. Absorbing knowledge across teams is not as easy as within teams, as the locus of knowledge resides outside team boundaries and thus limits its accessibility.

One may argue that knowledge diversity across teams could entail post-mobility performance benefits. The knowledge-based view argues that a firm's primary goal is to integrate the specialized knowledge of its employees (Aggarwal et al., 2020; Grant, 1996). Thus, the very purpose of a firm's existence may support having a high level of complementarity in the knowledge base between R&D teams. Examining patenting activities in optical disk technology, Rosenkopf and Nerkar (2001) find that knowledge exploration spanning technological and organizational boundaries has a greater technological impact relative to local searches.

Yet a high level of across-team diversity can pose *disadvantages* for employees for two key reasons. First, at firms with greater across-team diversity, a focal employee has more distant knowledge experience and routines from other teams (Hansen, 2002), reducing knowledge spillover and learning benefits. The complexity of knowledge, that is, the degree to which a piece of knowledge comprises many elements requiring rich interaction or the level of difficulty of recombining elements (Simon, 1991), could make a knowledge recipient resist knowledge transfer and, thus, reduce knowledge diffusion (Ethiraj & Levinthal, 2004; Sorenson, Rivkin, & Fleming, 2006). According to the absorptive capacity argument, prior possession of relevant knowledge and skills is what gives rise to creativity (Cohen & Levinthal, 1990). While existing knowledge that is too similar to the knowledge being acquired may contribute little to learning and innovation, existing knowledge must at the same time be relevant enough that the diverse technological knowledge of collaborators can be absorbed and applied to generate new ideas. The lack of absorptive capacity may not be an issue for within-team diversity but for across-team diversity, given the assumption that knowledge diversity from different teams becomes too distant and irrelevant for knowledge recipients to absorb and make relevant to their own use.[5] As information and routines become more dispersed, the cost for an individual to integrate knowledge increases, impeding knowledge creation (Kogut & Zander, 1992; Mors, 2010). Scholars have shown that an organization's subunits perform well to the extent that they retain related competencies that can be used across multiple subunits (Markides & Williamson, 1994).

Second, higher across-team diversity increases across-team coordination costs, as knowledge sharing is less likely to occur naturally. To take advantage of a diverse set of technological knowledge present across teams within a firm, an individual must seek out and acquire information from others, then digest it for their own use (Cohen & Levinthal, 1990). Such costs are much higher at firms with high average across-team diversity. Prior studies on knowledge management find that network connections facilitate knowledge transfers and synergies across a firm's business units (Kogut & Zander, 1992; Singh, 2005). For example, intra-regional and intra-firm knowledge flows are stronger than flows across firms and regions (Singh, 2005). Whereas knowledge sharing naturally and automatically occurs among members within a team,[6] an employee needs to conduct an active search to access new information from socially distant actors (Hansen, Mors, & Lovas, 2005). These searches are even more difficult and costly for external hires, as they often lack the common skills, routines, and languages possessed by incumbent employees. New arrivals also have fewer social ties outside of their own R&D teams. Besides the costs associated with distant knowledge searches, interactions with members outside their own teams could interfere with internal coordination within teams (Hansen, 1999). Introducing external and diverse knowledge could make it difficult for individuals to agree when they integrate knowledge and make important choices for the invention. As such, a diverse set of knowledge allocated across teams may be detrimental to external hires and their teammates' learning.

Hypothesis (H2a). *External hires who move to firms with higher levels of across-team knowledge diversity will, on average, experience lower innovation performance compared to those who move to firms with lower levels of across-team knowledge diversity.*

Hypothesis (H2b). *Teammates at firms with higher levels of across-team knowledge diversity will, on average, experience lower innovation performance compared to those at firms with lower levels of across-team knowledge diversity.*

3 | EMPIRICAL STRATEGY

3.1 | Patent data and mobility

Understanding the link between mobility and knowledge flows presents multiple empirical challenges, as researchers need comparable performance records before a move, as well as observations

[5]Appendix Table B2 shows that the average dyadic knowledge distance between members within a team is, on average, much smaller than the distance between members across teams (0.52 vs. 0.79). The complexity of knowledge appears to be a bigger problem for diversity across teams than within teams.

[6]Fleming, Colfer, Marin, and McPhie's (2003) field interviews suggest that patent collaboration teams meaningfully portray professional and personal ties among the inventors and that patent co-inventors often remain in touch even after applying for the patent. These ties are useful in the iterative knowledge search process: there are fewer errors when interpreting newly transmitted knowledge and a knowledge recipient can efficiently solicit advice from the knowledge provider (Sorenson et al., 2006). Moreover, these social ties contain tacit knowledge, a set of embedded knowledge distinct from explicit technological knowledge, such as common skills and shared language (Inkpen & Tsang, 2005; Lam, 2000; Polanyi, 1966).

on a large number of individuals working in the same field. Longitudinal data of detailed career histories are necessary to investigate changes in employee performance following a mobility event.

Patent data provide an attractive source of fine-grained information on each patent, including inventor and assignee firm names, application and grant dates, technological classifications, and backward and forward citations (Choudhury & Haas, 2018; Gruber et al., 2013; Mowery, Oxley, & Silverman, 1996; Palomeras & Melero, 2010; Singh & Agrawal, 2011; Somaya, 2012). These data bring several advantages to investigating my research questions. First, patent data provide historical accounts of inventors' past experiences, thus allowing researchers to track career histories. Second, patent citation and classification data offer several measures of innovation performance. Specifically, I introduce six measures of innovation performance to capture both the quantity and quality of inventions. Third, the large sample of inventors who move to a different firm at least once across a wide range of technology sectors increases the power of statistical tests while also rendering the results more generalizable than studies focusing on firms in a single sector.

3.2 | Constructing an interfirm mobility dataset

I use publicly available United States Patent and Trademark Office (USPTO) data to examine the link between team structure and innovative outcomes. This dataset contains information on all granted patents since 1975. While inventor and assignee firm names are available for each patent application, the data from USPTO do not offer a unique identifier for each inventor and assignee firm. Supported by the USPTO Office of the Chief Economist, the PatentsView website (www.patentsview.org) provides a reliable source for firm, inventor, and location disambiguation data based on algorithms devised by a team of scholars studying intellectual property, innovation, and technological change.

To detect mobility events, I track changes in firm identifiers on an inventor's successive patents (Almeida & Kogut, 1999; Singh & Agrawal, 2011; Song et al., 2003). I start with the sample of all U.S. utility patents from 1975 to 2017 and then chronologically trace applied patents. I restrict the sample to patents with a single firm, as it is difficult to infer employer of an inventor if there are multiple assignee firms for a patent. The sample is limited to inventors who have moved between U.S. companies or corporations, excluding those who have worked for the government or as independent inventors. From there, I construct a list of inventors who have changed employees.

Since my key variables are based on the inferred move date, results can be sensitive to the move window estimation. Even when I observe two successive patents by the same inventor but at different firms, I cannot pinpoint the exact move date. To overcome this challenge, I adopt Singh and Agrawal's (2011) approach wherein the "move date" is defined as the halfway point between the last patent application date at the previous firm and the first application at the new firm. I drop cases with move windows of four or more years, as the move date is too uncertain. This results in an initial set of 437,383 inferred mobility cases.

Given that the move could have taken place any time during the window, I use the calendar year of the inferred move date. Then, I remove mobility events in which an inventor has spent less than 1 year at either the departure firm or the destination firm. This restriction ensures a sufficient observation period to calculate performance metrics at both firms, yet leads to dropping about 60% of the initial set of mobility cases, yielding 166,408 observations. As a final step, I remove mobility events with an end date at the destination firm after 2012 to enable the calculation of 5-year forward citations of post-mobility patents. The initial sample consists of 120,549 mobility observations corresponding to 78,287 inventors at 27,933 firms.[7] The final sample used for analysis consists of 63,976 mobility cases across 4,697 firms. The sample size is reduced while calculating two firm-level team diversity measures and control variables (further discussed in Section 3.4).

3.3 | Post-mobility innovation performance and the role of team knowledge diversity

While existing studies have primarily focused on firm-level outcomes to capture the effect of mobility, I focus on the post-mobility performances of external hires and their teammates. Specifically, my main analyses focus on how a firm's team design structure shapes post-mobility performance. If mobility occurs at time t, I measure pre-mobility performance until time $t-1$ and post-mobility performance from time $t+1$; team design characteristics and control variables are measured at time t.[8]

Examining an individual's post-mobility performance as the outcome variable offers several methodological advantages. First, I can disentangle an external hire's performance contribution from knowledge spillover effects to teammates. Singh and Agrawal (2011) note that both recruits' exploitation of their own prior ideas, as well as diffusion to others, are simultaneously captured in firm-level outcomes. Measuring the contribution of external hires at the team- or firm-level may lead to an overestimation of the outcome. Second, when both explanatory variables and outcome variables are measured at the firm level, there can be potential endogeneity issues. An unobserved variable, such as a firm's corporate strategy (e.g., acquisitions, geographic expansion) or quality of management, may explain variation in both team diversity measures and the firm's innovation performance. Also, the design could be prone to reverse causality, whereby firm performance affects team structure, as discussed by Aggarwal et al. (2020, p. 11). The change in performance associated with R&D team design (at the time of the move) is less likely to be affected by the firm's strategic efforts when observed at the individual level. Despite many benefits, my design is subject to several potential selection biases (e.g., sorting of external hires into diverse firms), which I further discuss in Section 4.3.2.

To estimate the effects of team design on teammates' post-mobility performance, I pool a list of all individuals, who are part of the earliest collaborative team the new hire joins, and track how the teammate's innovation performance changes after collaborating with the focal

[7]Although the final sample is 30% of my initial sample of mobility events, I do not expect my results to be systematically different. Rather, including cases in which inventors have spent less than a year at the departure or destination firm could bias my estimates, as early departure may be correlated with high or low performance. That is, inventors with short tenures could be superstars frequently poached by firms or low-quality inventors who are laid off. Research and patent applications typically take at least a year, thus patent outputs for these inventors could appear to be zero even if the inventor played an active role in a new invention. Removing events after 2012 should not affect the results. I include move year fixed effects in all of my models to account for time trends.

[8]I conceptualize team knowledge diversity as given (or stable) in the short-term at the time of the move. For instance, it would be difficult and costly for firms to change team structure with the arrival of one external hire. Also, adjusting team structure too often could be disruptive to the firm and deter coordination among employees. Thus, it is reasonable to assume that team structure remains rather stable at least in the short term. However, in the longer term, team structures could evolve to the extent that team membership is highly fluid and employees have agency in choosing with whom to collaborate.

inventor.[9] I identify a total of 42,362 teammates corresponding to 31,056 external hires. There are missing teammates if the focal inventor does not have more than one patent or a collaborator at the destination firm, and if all of a hire's teammates joined after or left before the hire.

For external hires, I examine post-mobility performance at the destination firm throughout the hire's tenure, taking into account their performance at the departure firm. For teammates, I examine their performance during the 2 years after the focal inventor joined the firm, controlling for 2-year performance prior to working with the new hire. I chose the 2-year time frame for the main model because many inventors in my sample move within 3 years (approximately 65% of my sample) and longer windows introduce more noise into my estimation. Further, a teammate may be exposed to more than one external hire, making it difficult to capture the focal hire's contributions. Nonetheless, in Section 4, I show estimates when the outcomes are measured over the longer term.

3.4 | Measures

3.4.1 | Innovation performance

Firms have different strategic goals and preferences for how to improve innovation performance. For example, some firms apply for as many patents as possible in order to demonstrate market dominance in a given technology sector. Other firms focus on producing one "breakthrough innovation," emphasizing singular quality over quantity. Thus, I consider six different measures that capture innovation performance.[10] The first dependent variable, *number of patents*, serves as a proxy for productivity and measures the count of all patents produced after a mobility event.

The number of forward citations has been widely used as a measure of the technological impact and the economic value of a patent invention (Jaffe & De Rassenfosse, 2017). I derive *forward citations* using the number of forward citations received within the 5-year post-application period for each patent and then calculating the average of the counts. The distribution of citation counts ranges from 0 to 1,051, has a median of 6.4, and is heavily skewed to the right. Thus, in addition to considering *average* citations, I also consider the *distribution* of citations—specifically, "breakthrough" innovations and those with minimal impact (Singh & Fleming, 2010). I create two binary variables: *top 5 percent cite* and *zero cite*. *Top 5 percent cite* takes a value of one if at least one of the patents produced at the destination firm is in the top

[9]While I considered observing performance change at the team-level, team membership is typically not stable across time within a firm. For example, teams are often assigned on a project-basis and so the same set of inventors typically does not appear more than once. Thus, I explore how the focal hire impacts teammate performance after the mobility event.

[10]While most of the dependent variables are not highly correlated with each other, I find strong pairwise correlations between the (a) *number of new tech classes* and *number of patents* ($\rho = 0.65$) and (b) *number of new tech classes* and *tech diversity* ($\rho = 0.66$). This is not surprising given that new technological class acquired is associated with the number of patents produced at the new firm. Yet the two outcomes have different implications: the degree of learning or acquisition of new technical knowledge for the former, and productivity at the destination firm for the latter. Also, the *number of new tech classes* is strongly linked with *tech diversity*, because the knowledge diversity calculation is dependent on the total number of technological classes. While the *number of new tech classes* informs the extent of learning at the destination firm, *tech diversity* serves as a measure of patent novelty. I explore the six innovation performance measures separately, as each performance measure has distinct strategic implications for firm strategy.

5% of 5-year forward citations in a given application year and technology class. *Zero cite* is set to 1 if all of an inventor's post-mobility patents receive no citations.

To examine the breadth of technological fields capturing the extent of *learning* and the *novelty* of patents, I construct two additional dependent variables: *tech diversity* and *number of new tech classes*. *Number of new tech classes* measures the number of new technological fields the inventor has entered after joining the new firm, while *tech diversity* measures the degree of technological recombination. I follow the previous literature and use 1 minus the Herfindahl–Hirschman index (HHI) of concentration of post-mobility patents across different technological classes (Marx et al., 2009; Trajtenberg, Henderson, & Jaffe, 1997). For an inventor i with J patents that are associated with technological areas $k=(1,\cdots,K)$, the diversity measure using HHI can be defined as:

$$Tech\ diversity_i = 1 - \sum_{k=1}^{K} \left(\frac{\sum_{j=1}^{J} s_{jk}}{J} \right)^2, \tag{1}$$

where s_{jk} is the patent j's share of technology classifications associated with technological area k. If all of the patents build on knowledge from one patent class, knowledge diversity is equal to zero; it approaches one as patents cited are spread across more technological fields.

3.4.2 | Within-team diversity and across-team diversity

Within-team diversity of a destination firm captures the average dyadic diversity in technological fields *between inventors* within a given patent team. Across-team diversity measures the average dyadic diversity in technological fields *between teams*, showing how teams differ from one another in terms of employees' knowledge experience. The two-team diversity variables are measured at the move year to ensure that team compositions do not change based on new hires. A detailed description of how I compute the measures, as well as an illustrative example, can be found in Appendix A.

To calculate *within-team diversity*, I measure the angular distance between the knowledge experience vector of each pair of inventors within a team. The knowledge experience vector contains the count of patents produced in each technology category. I consider all technology experience gained throughout an inventor's career.[11] Then, I take the average of each patent team's team-level value to calculate firm-level average within-team diversity. For *across-team diversity*, I calculate the angular distance between the knowledge experience vector of each pair of patent teams within a firm. Instead of calculating a vector for each individual, I create a knowledge experience vector for each team, adding up the teammates' experience in different technological fields throughout their careers. To calculate firm-level average across-team value, I take the average of the pairwise distance between each pair of teams.

[11] Analyses using the diversity measures based on 3- and 5-year career trajectories, which exhibit similar patterns as main analyses, are available upon request. I posit that knowledge acquired throughout one's career, not just from recent projects, best reflect the stock of knowledge that could be used for future knowledge production.

I identify R&D teams as sets of inventors who file for the same patent application (Aggarwal et al., 2020; Jensen, Kovács, & Sorenson, 2018; Singh, 2005). R&D team memberships are observed when the patent application is submitted, though there may be other teams within a given firm collaborating on a project not reflected in the data. Nonetheless, interviews with patent inventors and patent attorneys confirmed that the inventors in a patent application represents a typical R&D team within a firm.

In Figure 2, I illustrate the distribution of within-team and across-team diversity measures, which both range from 0 to 1, in my sample. Missing values occur in two cases. First, I cannot calculate diversity measures if a firm's number of patents or number of inventors in a move year is less than 2. Second, diversity measures cannot be calculated if the number of previous patents by an inventor is less than 2 and if there is only one inventor with previous patents (the diversity score will automatically be zero). Thus, these observations are marked as missing. The partial correlation between the two diversity measures is between 0.3 and 0.4 (Appendix Table C1). I conduct analyses using the two diversity measures together in a model and separately in different models to ensure that the correlation between the two variables is not driving the results. As shown in the scatterplot, firms are dispersed across the four quadrants.

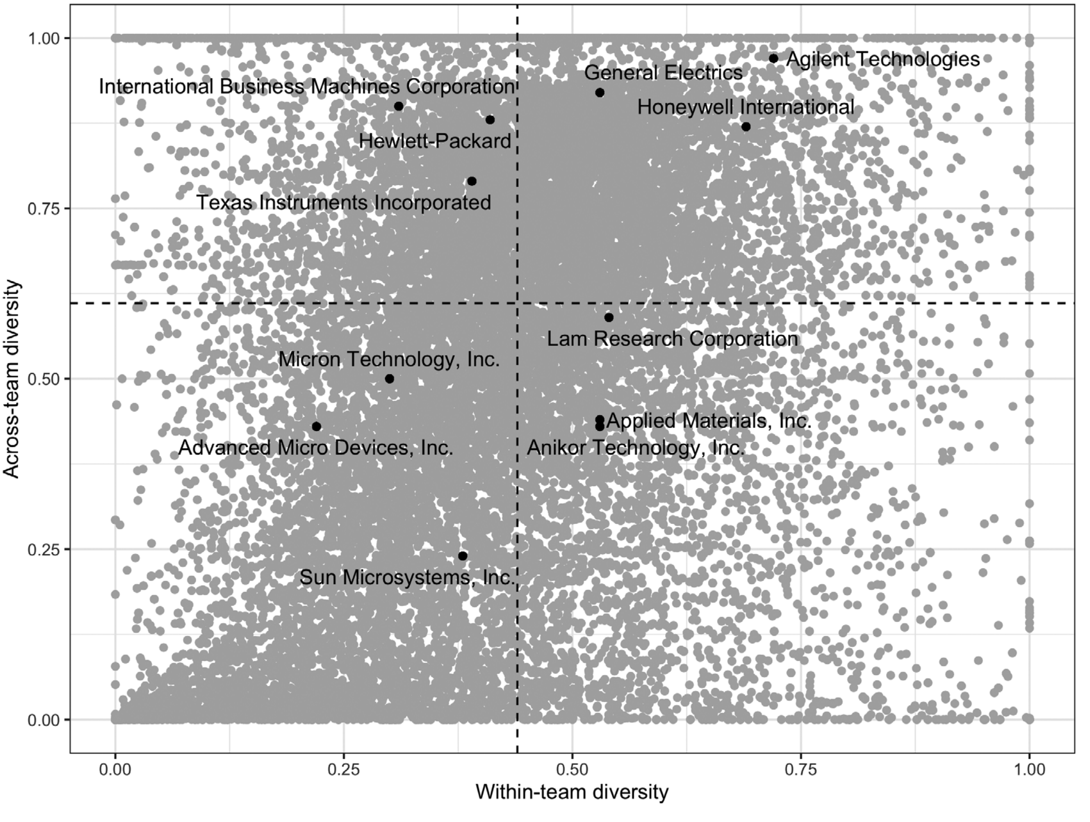

FIGURE 2 Distribution of within-team and across-team diversity. Each dot represents the within-team diversity (x-axis) and across-team diversity (y-axis) values for each firm-year observation used in Table 4 (n = 63,976). Here, I also provide examples of firms engaging in R&D activities in the semiconductor technology (National Bureau of Economic Research [NBER] subcategory of 46) with high or low within-team and across-team diversity. Among firms conducting research in the semiconductor space, the average within-team diversity score is 0.47, while the average across-team diversity score is 0.71.

3.4.3 | Control variables

Pre-mobility performance

To capture change in the performance of an external hire and their teammates after mobility, I use post-mobility performance as the dependent variable and control for pre-mobility innovation performance. Since each dependent variable reflects different ways of understanding innovation performance, I include a pre-mobility performance control relevant to the specific dependent variable. For models with post-mobility number of patents as outcome variables, I use *pre–mobility number of patents* to account for the innovation productivity at the departure firm. For the three dependent variables that use forward citations, I use *pre–mobility forward citations*, average forward citations of patents produced at the prior firm. I include *pre–mobility number of tech classes* and *pre–mobility tech diversity* for models on post-mobility *number of tech classes* and *tech diversity*, respectively.

Destination firm characteristics

I control for several firm-level characteristics that can simultaneously influence mobility, team design, and innovation performance. Instead of measuring these firm characteristics during the move year, I take the average over a three-year window, from 1 year before to 1 year after the move year. This approach smooths out potential noise from year-to-year fluctuations. I measure *firm age* as the number of years since a firm's first patent application date; *firm size* as the total number of patents applied; *firm number of inventors* as the unique number of inventors; and *firm scope* as the number of unique technological (main) classes of patents produced at the observed year. Team size could affect the diversity level and performance, thus I control for *firm team size*, the average team size for all patent teams applied at the observed year. Inventors who join firms with a high level of growth could appear to be more productive because the firm is growing faster than average. Thus, I also control for *firm growth rate*, measured using a 3-year compound annual growth rate —1 year before the move year as the beginning year and 1 year after the move year as the end year—of patents produced at the destination firm. The organization of R&D across geographic spaces is an important determinant of firm-level innovation (Chacar & Lieberman, 2003). I also control for *firm geodiversity*, or the degree of geographic diversity (or concentration), calculated using the Herfindahl index (based on Equation (1) to examine the distribution of R&D locations at the state level).

Mobility characteristics

To enable a systematic comparison across different inventors with varying tenures at their departure and destination firms, I control for *tenure at destination* and *tenure at departure*, measured as the number of years an inventor spent at the destination firm and departure firm, respectively. I also control for an inventor's *R&D experience*, or the number of years since an inventor's first patent application date. I also control for *move window*, the time period between the last patent application filed at the departure firm and the first patent application filed at the destination firm, to account for the increased uncertainty with longer move windows.[12]

[12]Inaccurate midpoint estimations may systematically bias the estimates. The coefficient should be close to zero if the inferred move year is accurate; negative if, on average, the actual entry to the destination firm is earlier than the inferred move year; and positive if, on average, the actual entry to the destination firm is later than the inferred move year.

Table 1 presents the summary statistics for the external hire and teammate samples. Table 2 presents the pairwise correlations for the external hire sample in Panel (a) and teammate sample in Panel (b). Table 3, Panel (a), shows team knowledge diversity statistics by three key firm characteristics: firm size, average team size, and firm growth rate. Table 3, Panel (b), depicts how team composition varies by team diversity.

3.4.4 | Preferred regression models

The two dependent variables, *number of patents* and *number of tech classes*, are measured as counts and skewed to the right. Counts cannot fall below zero, thus linear regression models may yield inefficient and biased estimates. I therefore use Poisson quasi-maximum likelihood estimator (QMLE) for these variables.[13] The default log-link function is used for the quasi-Poisson distribution, so I log the continuous independent variables for ease of interpretation. This allows me to interpret the coefficients as elasticities. For continuous-dependent variables, I use ordinary least squares regression models. For the model using *forward citations*, I employ log–log regression: the dependent variable is logged as the distribution is heavily skewed to the right; the explanatory variables are also in log form for constant elasticity.

For the main analyses examining the role of R&D team design, I employ robust *SE*s clustered at the destination firm level. I also add move year and technology fixed effects. The move year dummies are used to control for differences in the calendar year in which employees move to another firm. Since mobility and citation patterns may vary substantially across different technological fields, I include the National Bureau of Economic Research (NBER) technology area subcategory as dummy variables. For individuals who have worked in multiple technological fields, I chose the last technological field before the mobility event, which should be reflective of the technology or industry that they will work in at the new firm. Using World Intellectual Property technology fields or cooperative patent classification for technology field dummies yields similar results.

4 | RESULTS

4.1 | Average post-mobility performances of external hires and teammates

Before testing the hypotheses on team knowledge diversity, I first investigate the average performance consequences of external hires and team members following a mobility event. Understanding this baseline allows us to identify boundary conditions of the main effects of team design and to understand the mechanisms that shape the post-mobility performances of hires and teammates. In Appendix B, I provide details on my estimation strategy and results from the baseline analyses.

[13]Scholars have commonly employed Poisson or negative binomial models for estimating parameters. Compared to the negative binomial model, the Poisson model is more robust to distributional misspecification if the conditional mean is correctly specified (Cameron & Trivedi, 2013). The Poisson model, however, relies on a strong assumption that the conditional mean and variance are the same. In my data, the variances of the dependent variables are larger than the means. Thus, the Poisson QMLE, which relaxes the assumption of the classic Poisson model and better accounts for the over-dispersion parameter, is employed (Kang & Lee, 2022).

TABLE 1 Descriptive statistics

Statistic	*N*	Mean	*SD*	Min	Max
External hire characteristics					
Post-mobility performance					
Number of patents	63,976	3.19	4.84	0.00	160.00
Forward citations	62,417	17.92	39.99	0.00	1,051.00
Top 5% cite	62,417	0.09	0.29	0.00	1.00
Zero cite	62,417	0.19	0.39	0.00	1.00
Number of new tech classes	62,417	1.02	1.34	0.00	20.00
Tech diversity	62,417	0.22	0.28	0.00	0.92
Pre-mobility performance					
Number of patents	63,976	7.62	9.71	1.00	284.00
Forward citations	63,976	31.74	50.59	0.00	1,254.80
Number of tech classes	63,976	3.29	2.51	1.00	77.00
Tech diversity	63,976	0.46	0.28	0.00	0.96
Mobility characteristics					
Tenure at destination	63,976	3.74	3.05	1.00	34.96
Tenure at departure	63,976	3.47	3.23	1.00	31.80
R&D experience	63,976	7.43	6.17	0.00	36.00
Move window	63,976	659.17	401.29	0.00	1,459.00
Destination firm characteristics					
Knowledge diversity					
Within-team diversity	63,976	0.44	0.16	0.00	1.00
Across-team diversity	63,976	0.62	0.26	0.00	1.00
Other characteristics					
Firm age	63,976	31.83	9.54	8.00	42.00
Firm size	63,976	147.65	309.94	0.67	2,253.67
Firm number of inventors	63,976	262.93	553.31	1.00	3,881.00
Firm scope	63,976	21.44	24.46	0.33	129.67
Firm geodiversity	63,976	0.07	0.15	0.00	0.85
Firm growth rate	63,976	0.38	0.52	0.00	6.07
Firm team size	63,976	2.84	0.91	1.12	13.71
Teammate characteristics					
Tenure (pre-mobility)	42,362	4.87	5.45	0.00	34.26
Tenure (post-mobility)	42,362	6.36	4.77	0.00	34.08
R&D experience	42,362	11.16	7.41	0.00	36.00
Knowledge distance	33,099	0.52	0.35	0.00	1.00
Post-mobility performance					
Number of patents	42,362	3.99	9.99	0.00	405.00
Forward citations	25,348	22.22	41.81	0.00	906.00

TABLE 1 (Continued)

Statistic	*N*	Mean	*SD*	Min	Max
Top 5% cite	25,348	0.24	0.43	0.00	1.00
Zero cite	25,348	0.50	0.50	0.00	1.00
Number of new tech classes	25,348	1.57	1.72	0.00	40.00
Tech diversity	25,348	0.39	0.29	0.00	0.97
Pre-mobility performance					
Number of patents	42,362	3.17	8.47	0.00	362.00
Forward citations	22,136	28.97	52.35	0.00	898.50
Number of tech classes	22,136	2.74	2.80	1.00	86.00
Tech diversity	22,136	0.38	0.30	0.00	0.97

Note: The external hire statistics and teammate statistics are based on the complete case sample used for Model 1 in Tables 4 and 5. The pre-mobility and post-mobility performances of external hires are captured throughout their tenure at the destination or departure firm, while those of teammates are captured during the 2-year period before and after the move year.

To summarize, I find that external hires experience an improvement in performance, while the performance of their teammates at new firms exhibit divergent patterns (Appendix Table B3). External hires have 71.8% greater productivity, 41.9% more average forward citations, 15.3% more technological fields learned, and greater novelty of patents than individuals who do not switch firms ($p<.01$). Teammates, compared to individuals who do not work with external hires, produce 16.1% fewer patents ($p<.001$). This productivity decline may be associated with the coordination costs from working with external hires. But the inventions they do produce have greater technological impact: average forward citations and the likelihood of breakthrough innovation increase by 9.4% ($p=.017$) and 1.0% ($p=.022$).

4.2 | Main results: R&D team design and post-mobility performance

Tables 4 and 5 provide results related to Hypotheses (H1a), (H1b), (H2a), and (H2b) regarding how the two design factors contribute to the post-mobility performances of external hires and their teammates.

For external hires, Models 1–6 in Table 4 suggest that a 1 *SD* increase in within-team diversity is associated with: 0.8% greater likelihood of creating a breakthrough innovation ($\frac{0.021\times0.16}{0.44\times0.01}$), 2.5% more technological domains learned at the new firm, and an increase in the combination novelty of patents ($p<.05$). In contrast, a standard deviation increase in across-team diversity is associated with: 0.6% lower productivity ($\frac{-0.015\times0.26}{0.62\times0.01}$), 3.0% fewer average forward citations, 2.3% decline in the likelihood of "breakthrough" innovation, 2.0% greater chance of not receiving any citation, and small declines in the number of new technological fields learned and the combination novelty ($p<.01$).

The relationship between the two diversity measures and the 2-year post-mobility performances of teammates exhibits similar pattern. Table 5 shows that a 1 *SD* increase in within-team diversity is associated with: a 3.1% decline in the likelihood of producing only zero-impact inventions, a 4.3% increase in the number of new technological classes learned, and a greater combination novelty of patents produced ($p<.01$). A 1 *SD* increase in across-team diversity is linked with: 2.2% lower average citation impact, 3.6% lower likelihood of creating breakthrough

TABLE 2 Pairwise correlations

Panel (a)—Sample of external hires	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Number of patents												
(2) Forward citations	0.02											
(3) Top 5% cite	0.26	0.43										
(4) Zero cite	−0.16	−0.18	−0.14									
(5) Number of new tech classes	0.65	0.03	0.20	−0.15								
(6) Tech diversity	0.50	−0.01	0.17	−0.22	0.66							
(7) Within-team diversity	0.00	0.00	0.00	−0.02	0.09	0.05						
(8) Across-team diversity	0.01	−0.05	−0.05	−0.05	0.09	0.05	0.39					
(9) Tenure at destination	0.52	0.01	0.14	−0.15	0.49	0.44	0.03	0.08				
(10) Tenure at departure	0.02	−0.02	−0.01	−0.01	0.00	0.01	0.04	0.02	0.02			
(11) R&D experience	−0.01	−0.05	−0.01	0.03	−0.09	0.00	0.03	−0.01	−0.10	0.44		
(12) Move window	−0.05	−0.02	−0.04	0.03	0.05	−0.07	0.02	0.06	0.13	−0.01	−0.14	
(13) Firm age	0.03	0.07	−0.01	−0.09	0.08	0.03	0.03	0.29	0.11	−0.06	−0.06	0.04
(14) Firm size	0.04	−0.06	−0.02	0.03	0.06	0.06	0.07	0.25	−0.02	−0.04	−0.02	0.01
(15) Firm number of inventors	0.03	−0.06	−0.02	0.04	0.04	0.04	0.08	0.25	−0.03	−0.04	−0.01	0.01
(16) Firm scope	0.08	−0.04	−0.02	−0.04	0.15	0.12	0.16	0.47	0.07	−0.02	−0.02	0.04
(17) Firm geodiversity	−0.01	0.02	0.00	0.00	−0.01	−0.01	−0.04	0.03	0.01	−0.01	−0.01	0.02
(18) Firm growth rate	0.08	0.04	0.02	−0.07	0.08	0.10	0.05	0.01	0.11	0.12	−0.05	−0.01
(19) Firm team size	−0.06	−0.06	0.01	0.15	−0.10	−0.06	−0.11	−0.28	−0.14	0.01	0.08	−0.07
(20) Number of patents (pre-mobility)	0.04	−0.05	0.01	0.02	−0.11	0.04	−0.01	−0.04	−0.10	0.14	0.52	−0.16
(21) Forward citations (pre-mobility)	0.02	0.37	0.16	−0.03	0.00	0.01	−0.02	−0.08	0.01	−0.04	−0.01	−0.01
(22) Number of tech classes (pre-mobility)	0.02	−0.06	0.00	0.03	−0.09	0.06	0.06	0.02	−0.11	0.16	0.60	−0.17
(23) Tech diversity (pre-mobility)	0.00	−0.06	0.00	0.04	−0.08	0.06	0.08	0.02	−0.12	0.20	0.49	−0.23

TABLE 2 (Continued)

Panel (a)—Sample of external hires												
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	
(14) Firm size	0.09											
(15) Firm number of inventors	0.11	0.97										
(16) Firm scope	0.25	0.74	0.71									
(17) Firm geodiversity	0.05	−0.09	−0.10	−0.07								
(18) Firm growth rate	−0.39	−0.09	−0.10	−0.06	−0.04							
(19) Firm team size	−0.17	0.02	0.07	−0.11	−0.05	−0.05						
(20) Number of patents (pre-mobility)	−0.07	0.01	0.02	−0.02	−0.02	−0.04	0.08					
(21) Forward citations (pre-mobility)	−0.04	−0.01	−0.02	−0.03	0.02	0.04	−0.01	0.00				
(22) Number of tech classes (pre-mobility)	−0.05	0.04	0.04	0.02	−0.03	−0.06	0.06	0.74	−0.03			
(23) Tech diversity (pre-mobility)	−0.05	0.04	0.05	0.03	−0.03	−0.06	0.06	0.39	−0.05	0.73		

Panel (b)—Sample of teammates												
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
(1) Number of patents												
(2) Forward citations	−0.01											
(3) Top 5% cite	0.28	0.35										
(4) Zero cite	0.24	−0.23	0.13									
(5) Number of new tech classes	0.52	0.01	0.18	0.17								
(6) Tech diversity	0.28	−0.01	0.22	0.30	0.59							
(7) Within-team diversity	−0.06	0.00	−0.03	−0.07	0.11	0.06						
(8) Across-team diversity	−0.09	−0.05	−0.08	−0.11	0.09	0.01	0.45					
(9) Tenure at destination	0.12	0.13	0.11	−0.02	0.12	0.14	0.01	0.04				
(10) Tenure at departure	0.06	−0.07	0.02	0.08	0.01	0.04	−0.01	0.04	0.02			
(11) R&D experience	0.14	−0.10	0.04	0.16	0.03	0.07	−0.01	−0.08	−0.09	0.44		

TABLE 2 (Continued)

Panel (b)—Sample of teammates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(12) Move window	−0.03	0.01	−0.01	−0.03	0.00	−0.02	0.02	0.06	0.10	0.01	−0.04	
(13) Firm age	−0.08	0.06	−0.09	−0.18	0.00	−0.05	0.06	0.29	0.10	0.34	−0.07	0.05
(14) Firm size	0.05	−0.07	0.03	0.11	0.13	0.09	0.11	0.31	0.05	0.13	−0.03	0.02
(15) Firm number of inventors	0.03	−0.07	0.03	0.11	0.11	0.07	0.12	0.31	0.04	0.16	−0.01	0.01
(16) Firm scope	0.02	−0.05	−0.02	−0.01	0.17	0.11	0.22	0.54	0.12	0.14	−0.04	0.04
(17) Firm geodiversity	−0.01	0.02	−0.01	−0.03	−0.03	−0.01	−0.06	0.01	−0.01	−0.06	−0.01	0.01
(18) Firm growth rate	0.02	0.07	−0.01	−0.09	0.03	0.02	0.04	−0.01	0.05	−0.36	−0.06	−0.07
(19) Firm team size	0.06	−0.07	0.04	0.21	−0.03	0.02	−0.14	−0.30	−0.09	0.12	0.25	−0.06
(20) Number of patents (pre-mobility)	0.80	−0.03	0.22	0.20	0.30	0.23	−0.06	−0.10	0.09	0.07	0.15	−0.04
(21) Forward citations (pre-mobility)	0.01	0.65	0.22	−0.11	0.02	0.04	−0.01	−0.08	0.12	−0.08	−0.09	0.01
(22) Number of tech classes (pre-mobility)	0.70	−0.04	0.20	0.21	0.45	0.32	0.03	−0.01	0.06	0.06	0.15	0.00
(23) Tech diversity (pre-mobility)	0.25	−0.05	0.16	0.23	0.16	0.38	0.05	−0.01	0.05	0.09	0.16	−0.02
	(13)	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**	**(23)**	
(14) Firm size	0.11											
(15) Firm number of inventors	0.14	0.98										
(16) Firm scope	0.25	0.74	0.71									
(17) Firm geodiversity	0.00	−0.11	−0.12	−0.08								
(18) Firm growth rate	−0.42	−0.10	−0.12	−0.07	−0.02							
(19) Firm team size	−0.14	0.01	0.06	−0.12	−0.06	−0.05						
(20) Number of patents (pre-mobility)	−0.08	0.04	0.03	0.01	−0.01	0.00	0.07					
(21) Forward citations (pre-mobility)	0.01	−0.06	−0.06	−0.05	0.02	0.07	−0.04	−0.01				
(22) Number of tech classes (pre-mobility)	−0.07	0.11	0.10	0.09	−0.02	−0.01	0.05	0.80	−0.03			
(23) Tech diversity (pre-mobility)	−0.08	0.09	0.08	0.08	−0.02	−0.01	0.07	0.34	−0.05	0.61		

TABLE 3 Team design characteristics by firms

Panel (a)—Team knowledge diversity by firm characteristics			
	Within-team diversity	**Across-team diversity**	**Average inventor tenure**
Firm size			
Small	0.43 ± 0.22	0.48 ± 0.32	6.89 ± 3.28
Medium	0.43 ± 0.14	0.63 ± 0.23	6.69 ± 2.64
Large	0.45 ± 0.09	0.73 ± 0.17	6.60 ± 2.16
Firm average team size			
Small	0.45 ± 0.17	0.67 ± 0.27	5.80 ± 2.77
Medium	0.44 ± 0.15	0.63 ± 0.24	6.82 ± 2.50
Large	0.42 ± 0.16	0.54 ± 0.28	7.56 ± 2.64
Patent growth rate			
Low	0.44 ± 0.15	0.66 ± 0.25	7.81 ± 2.61
Medium	0.42 ± 0.16	0.59 ± 0.26	6.36 ± 2.70
High	0.45 ± 0.16	0.61 ± 0.27	6.00 ± 2.56

Panel (b)—Knowledge diversity by team compositions		
	Average inventor tenure	**Average team size**
Within-team diversity		
High	6.70 ± 2.58	2.74 ± 0.73
Low	6.75 ± 2.87	2.93 ± 1.04
Across-team diversity		
High	6.37 ± 2.41	2.63 ± 0.61
Low	7.10 ± 2.99	3.05 ± 1.09

Note: The statistics in Panel (a) show the mean and *SD* of within-team diversity, across-team diversity, and average inventor tenure values in each group. The tercile cut-off points for firm size are (0.67; 14.67; 74.67; 2,253.67). The tercile cut-off points for average team size are (1.13, 2.41, 3.00, 13.71). The tercile cut-off points for patent growth rate (3-year CAGR) are (0.00, 0.09, 0.32, 6.07). The statistics in Panel (b) show the mean and *SD* for firms with high or low within-team and across-team diversity values. The cut-off points are determined using the median values of within-team diversity and across-team measures 0.44 and 0.68.
Abbreviation: CAGR, compound annual growth rate.

innovation, and less combination novelty of patents produced ($p<.01$). I also examine the role of knowledge diversity in the longer-term (3-year period and throughout tenure) performance of teammates and find that the associations are robust and consistent (Appendix Table C2). When I compare the estimates of knowledge diversity on the performances of external hires and teammates throughout tenure, I do not find any evidence that knowledge diversity is more important for one population than the other. Yet my results suggest strong and consistent associations between the two dimensions of diversity and employees' post-mobility innovation performance.[14] The opposing signs of within-team and across-team diversity inform managers

[14]In unreported regressions available upon request, I include within-team and across-team diversity in separate models to ensure that the correlation between the two main independent variables is not driving the results. I observe congruent results across all innovation measures, despite slightly smaller coefficients.

TABLE 4 Knowledge diversity and post-mobility innovation performance of external hires

Dependent variable	**Number of patents**	**Forward citations**	**Top 5% cite**	**Zero cite**	**Number of new tech classes**	**Tech diversity**
Model specification	**Poisson (link = log) (1)**	**OLS (log–log) (2)**	**OLS (3)**	**OLS (4)**	**Poisson (link = log) (5)**	**OLS (6)**
Within-team diversity	0.012 (0.013)	0.024 (0.033)	0.021 (0.011)	0.006 (0.013)	0.069 (0.015)	0.045 (0.009)
Across-team diversity	−0.015 (0.005)	−0.072 (0.024)	−0.055 (0.008)	0.048 (0.011)	−0.014 (0.005)	−0.035 (0.007)
Number of patents (pre-mobility)	0.236 (0.010)					
Forward citations (pre-mobility)		0.100 (0.010)	0.001 (0.000)	0.000 (0.000)		
Number of tech classes (pre-mobility)					−0.047 (0.013)	
Tech diversity (pre-mobility)						0.090 (0.005)
Tenure at departure	−0.022 (0.010)	−0.277 (0.040)	−0.001 (0.000)	0.002 (0.001)	0.055 (0.010)	−0.002 (0.000)
Tenure at destination	0.945 (0.014)	0.724 (0.052)	0.014 (0.001)	−0.012 (0.001)	0.680 (0.012)	0.041 (0.001)
Move window	−0.055 (0.004)	−0.176 (0.021)	−0.000 (0.000)	0.000 (0.000)	−0.029 (0.004)	−0.000 (0.000)
R&D experience	−0.143 (0.013)	0.191 (0.038)	0.000 (0.000)	−0.002 (0.000)	−0.105 (0.011)	−0.000 (0.000)
Firm age	0.065 (0.038)	−0.287 (0.205)	−0.000 (0.000)	0.001 (0.000)	0.090 (0.046)	−0.000 (0.000)
Firm size	0.572 (0.034)	1.423 (0.173)	−0.000 (0.000)	−0.000 (0.000)	0.332 (0.043)	0.000 (0.000)
Firm number of inventors	−0.481 (0.037)	−1.799 (0.222)	0.000 (0.000)	0.000 (0.000)	−0.402 (0.053)	−0.000 (0.000)
Firm scope	−0.057 (0.033)	0.613 (0.215)	0.000 (0.000)	−0.001 (0.000)	0.213 (0.047)	0.001 (0.000)
Firm geodiversity	0.000 (0.001)	−0.012 (0.008)	−0.000 (0.016)	0.023 (0.023)	−0.003 (0.001)	−0.006 (0.011)
Firm growth rate	0.045 (0.009)	−0.083 (0.043)	−0.005 (0.004)	0.004 (0.005)	0.020 (0.011)	0.025 (0.005)
Firm team size	0.368 (0.042)	1.560 (0.226)	0.007 (0.003)	0.002 (0.004)	0.310 (0.051)	−0.000 (0.002)
Constant	−0.478 (0.200)	2.251 (0.957)	0.108 (0.041)	0.038 (0.040)	−1.680 (0.243)	0.044 (0.038)
Observations	63,976	62,417	62,417	62,417	62,417	62,417
R^2		.196	.057	.156		.250

Note: The pre-mobility and post-mobility performances of external hires are captured throughout their tenure at the destination or departure firm. The team diversity measures and controls are included as logged values for the models on number of patents (1), forward citations (2), and number of technological classes (5). All models include technology class and move year fixed effects. Robust *SE*s, clustered at the destination firm level, in parentheses.
Abbreviation: OLS, ordinary least squares.

TABLE 5 Knowledge diversity and post-mobility innovation performance of teammates

Dependent variable	Number of patents	Forward citations	Top 5% cite	Zero cite	Number of new tech classes	Tech diversity
Model specification	Poisson (link = log) (1)	OLS (log–log) (2)	OLS (3)	OLS (4)	Poisson (link = log) (5)	OLS (6)
Within-team diversity	0.022 (0.019)	0.054 (0.057)	0.021 (0.031)	−0.084 (0.032)	0.119 (0.027)	0.086 (0.018)
Across-team diversity	−0.013 (0.010)	−0.052 (0.026)	−0.085 (0.022)	−0.024 (0.023)	−0.013 (0.008)	−0.038 (0.013)
Number of patents (pre-mobility)	0.191 (0.006)					
Forward citations (pre-mobility)		0.171 (0.014)	0.002 (0.000)	0.000 (0.000)		
Number of tech classes (pre-mobility)					0.316 (0.038)	
Tech diversity (pre-mobility)						0.334 (0.009)
Tenure (pre-mobility)	0.039 (0.005)	0.085 (0.012)	0.003 (0.001)	0.002 (0.001)	0.015 (0.003)	0.003 (0.001)
Move window	0.002 (0.010)	−0.004 (0.022)	−0.000 (0.000)	−0.000 (0.000)	−0.005 (0.007)	−0.000 (0.000)
R&D experience	0.138 (0.018)	0.035 (0.032)	0.000 (0.001)	0.001 (0.001)	0.007 (0.008)	0.001 (0.000)
Firm age	−0.003 (0.082)	−0.261 (0.196)	−0.002 (0.001)	−0.000 (0.001)	0.029 (0.052)	−0.001 (0.000)
Firm size	0.937 (0.049)	0.708 (0.120)	0.000 (0.000)	0.000 (0.000)	0.177 (0.047)	0.000 (0.000)
Firm number of inventors	−0.837 (0.052)	−0.781 (0.131)	−0.000 (0.000)	−0.000 (0.000)	−0.301 (0.044)	−0.000 (0.000)
Firm scope	−0.084 (0.051)	0.063 (0.101)	0.000 (0.000)	−0.000 (0.000)	0.265 (0.051)	0.001 (0.000)
Firm geodiversity	−0.002 (0.003)	−0.000 (0.007)	−0.007 (0.035)	−0.004 (0.036)	−0.006 (0.002)	0.017 (0.015)
Firm growth rate	0.064 (0.019)	0.017 (0.048)	−0.002 (0.011)	0.029 (0.013)	0.046 (0.011)	0.014 (0.006)
Firm team size	0.631 (0.087)	0.769 (0.208)	0.001 (0.006)	0.009 (0.005)	0.303 (0.062)	0.006 (0.003)
Constant	1.017 (0.402)	2.793 (0.812)	0.390 (0.110)	0.335 (0.108)	−0.202 (0.275)	0.251 (0.070)
Observations	42,362	21,264	21,264	21,264	21,264	21,264
R^2		.173	.096	.265		.209

Note: The pre-mobility and post-mobility performances of teammates are captured during the 2-year period before and after the move year. The team diversity measures and controls are included as logged values for the models on number of patents (1), forward citations (2), and number of technological classes (5). All models include technology class and move year fixed effects. Robust *SE*s, clustered at the destination firm level, in parentheses.
Abbreviation: OLS, ordinary least squares.

that, to maximize the post-mobility performances of hires and teammates, firms should separately consider two types of diversity when structuring their R&D teams.

To assist in the interpretation of the results, I demonstrate what 1 *SD* changes in within-team diversity and across-team diversity would look like in practice in Appendix A.

4.3 | Additional analyses

4.3.1 | Dyadic knowledge distance

Conditional on hiring a recruit, how should a firm assign the hire to existing teams? In developing Hypotheses (H1a) and (H1b), I suggested that higher within-team diversity is associated with greater knowledge benefits to external hires and their teammates, due to an increase in complementary knowledge assets. If so, we would expect assigning external hires to teammates with greater *dyadic knowledge distance*, compared to those with a similar knowledge base, to enhance the benefits to both parties. Also, the distant knowledge base further allows greater idea recombination opportunities, thereby increasing the likelihood of producing novel patents (Levinthal, 2016; Levitt & March, 1988; Maliranta, Mohnen, & Rouvinen, 2009). Examining the effect of knowledge distance thus allows me to confirm the underlying mechanisms for the hypothesis.

I calculate the dyadic knowledge distance between an external hire and their teammates (or non-teammates) at the time of move by using the cosine similarity measure (equation 2 in Appendix A) between the two individuals, and then subtracting it from 1 to calculate the distance. Table 6 shows that the post-mobility performances of both external hires (Panel a) and their teammates (Panels b and c) are positively associated with greater dyadic knowledge distance. Panel a shows that an increase of 1 *SD* in the knowledge distance (mean of 0.52 and *SD* of 0.35) can result in a 1–8% greater increase in the hires' performance ($p<.01$, except for the estimates in Models 2 and 4). Panel b shows that a 1 *SD* increase in knowledge distance is associated with by 2–8% ($p<.01$) improvement in teammates' post-mobility performance. Assigning external hires who possess more distant knowledge mitigates productivity loss (Appendix Table B3 Panel b) and allows collaborators to create more novel and valuable inventions.

4.3.2 | Endogeneity considerations

By examining an individual's change in performance due to variation in firm-level team structure at the time of a mobility event, my empirical strategy overcomes endogeneity concerns that arise when both explanatory and response variables occur at the firm level. However, several potential endogeneity issues remain, and I conduct several robustness checks to address these considerations.

The most plausible concern is that external hires with superior performance can choose to move to a firm with high within-team diversity and low across-team diversity. I examine the degree of self-sorting by (a) examining the correlations between pre-mobility characteristics and the two diversity measures and (b) conducting a coarsened exact matching (CEM) analysis among the sample of external hires and teammates, wherein the treatment variable is a binary variable indicating whether each knowledge diversity measure is above or below the median.

First, I assess whether external hires with certain pre-mobility characteristics systematically select into firms with high or low levels of within-team and across-team diversity (Appendix

TABLE 6 Knowledge distance and post-mobility innovation performance

Dependent variable	**Number of patents**	**Forward citations**	**Top 5% cite**	**Zero cite**	**Number of new tech classes**	**Tech diversity**
Model specification	***Poisson (link = log)*** **(1)**	***OLS (log–log)*** **(2)**	***OLS*** **(3)**	***OLS*** **(4)**	***Poisson (link = log)*** **(5)**	***OLS*** **(6)**
Panel (a)—Knowledge distance and the performance of external hires (throughout tenure)						
Knowledge distance	0.018 (0.004)	0.020 (0.015)	0.038 (0.008)	0.011 (0.005)	0.122 (0.008)	0.067 (0.006)
Constant	−0.790 (0.371)	3.350 (1.090)	0.316 (0.150)	0.014 (0.040)	0.147 (0.404)	0.083 (0.086)
Observations	33,099	32,800	32,800	32,800	32,800	32,800
R^2		.189	.084	.105		.302
Panel (b)—Knowledge distance and the short-term (2-yr) performance of teammates						
Knowledge distance	0.037 (0.005)	0.068 (0.012)	0.051 (0.009)	0.020 (0.009)	0.116 (0.005)	0.092 (0.005)
Constant	2.099 (0.324)	3.715 (0.886)	0.356 (0.099)	0.324 (0.102)	0.555 (0.250)	0.250 (0.061)
Observations	33,099	20,763	20,763	20,763	20,763	20,763
R^2		.172	.096	.264		.217
Panel (c)—Knowledge distance and the long-term (throughout tenure) performance of teammates						
Knowledge distance	0.044 (0.007)	0.042 (0.010)	0.053 (0.009)	0.053 (0.011)	0.111 (0.006)	0.062 (0.006)
Constant	4.432 (0.449)	5.017 (0.717)	0.265 (0.104)	0.768 (0.160)	2.510 (0.269)	0.287 (0.069)
Observations	33,099	20,227	20,227	11,553	20,227	20,227
R^2		.214	.084	.170		.212

Note: All models include control variables from Tables 4 and 5, technology class and move year fixed effects. The knowledge distance measure and controls are included as logged values in models regarding number of patents (1), forward citations (2), and number of technological classes (5). Robust *SE*s, clustered at the destination firm level, in parentheses.
Abbreviation: OLS, ordinary least squares.

Table C3). Overall, I find a minimal (near-zero) effect of sorting.[15] In addition to the small coefficient sizes, high-performing individuals select into firms with high levels of both within-team and across-team diversity (not firms with high within-team *and* low across-team diversity). This analysis also addresses another endogeneity concern, which relates to the possibility that firms make deliberate choices about whom to recruit. If firms strategically hire inventors based on their performance in order to improve knowledge diversity, we would expect high correlations between pre-mobility performance and diversity measures. Yet inventor performance before the move does not meaningfully predict diversity level at the destination firm.

Second, I conducted a CEM analysis to ensure the validity of my main analyses. Specifically, I categorized each individual in the hire/teammate sample into a treatment or control group, so

[15]A standard deviation increase in pre-mobility forward citations is associated with a 0.005 *SD* decrease in within-team diversity and a 0.024 *SD* decrease in across-team diversity. Compared to the effect sizes from the main analyses, the selection coefficients are marginal. For example, a 1 *SD* in across-team diversity is associated with a 3% decline ($\frac{-0.072\times0.26}{0.62\times0.01}$) in hires' post-mobility average forward citations (mean of 17.8) based on Table 5 Model 2. So, the 0.024 *SD* of across-team diversity from the partial correlation is associated with approximately 0.012 citations ($0.024\times0.03\times17.8$).

TABLE 7 CEM analysis of knowledge diversity and post-mobility innovation performance

Dependent variable	**Number of patents**	**Forward citations**	**Top 5% cite**	**Zero cite**	**Number of new tech classes**	**Tech diversity**
Model specification	**Poisson (link = log) (1)**	**OLS (log–log) (2)**	**OLS (3)**	**OLS (4)**	**Poisson (link = log) (5)**	**OLS (6)**
Panel (a)—The effect of high-within on external hires						
High-within (0/1)	0.028 (0.013)	−0.100 (0.063)	0.004 (0.002)	−0.006 (0.004)	0.111 (0.012)	0.129 (0.001)
Across-team diversity	−0.010 (0.005)	−0.102 (0.018)	−0.058 (0.006)	0.514 (0.008)	−0.005 (0.004)	−0.091 (0.002)
Constant	−0.006 (0.010)	−5.191 (0.717)	0.013 (0.001)	0.017 (0.002)	−1.880 (0.122)	0.235 (0.048)
Observations	63,870	62,041	62,041	62,041	61,954	62,362
Strata	487	587	587	587	364	567
R^2		.107	.028	.076		.262
Panel (b)—The effect of high-across on external hires						
High-across (0/1)	−0.038 (0.015)	−0.470 (0.075)	−0.024 (0.003)	0.009 (0.004)	−0.046 (0.015)	−0.050 (0.012)
Within-team diversity	0.007 (0.014)	−0.044 (0.032)	0.010 (0.008)	0.017 (0.013)	0.065 (0.013)	0.492 (0.032)
Constant	−0.040 (0.108)	−5.123 (0.736)	0.011 (0.012)	0.186 (0.021)	−1.769 (0.127)	0.042 (0.048)
Observations	63,825	61,977	61,977	61,977	61,934	62,319
Strata	479	579	579	579	366	561
R^2		.108	.028	.076		.264
Panel (c)—The effect of high-across on teammates						
High-within (0/1)	−0.017 (0.042)	−0.095 (0.086)	0.004 (0.010)	−0.047 (0.009)	0.139 (0.023)	0.031 (0.005)
Across-team diversity	−0.026 (0.010)	−0.095 (0.026)	−0.084 (0.018)	0.195 (0.022)	−0.001 (0.008)	−0.032 (0.005)
Constant	0.832 (0.324)	−2.148 (0.824)	0.385 (0.035)	0.652 (0.035)	0.064 (0.159)	0.341 (0.022)
Observations	42,165	21,091	21,091	21,091	21,068	21,050
Strata	487	587	587	587	364	567
R^2		.065	.036	.047		.056

TABLE 7 (Continued)

Dependent variable	**Number of patents**	**Forward citations**	**Top 5% cite**	**Zero cite**	**Number of new tech classes**	**Tech diversity**
Model specification	**Poisson (link = log) (1)**	**OLS (log–log) (2)**	**OLS (3)**	**OLS (4)**	**Poisson (link = log) (5)**	**OLS (6)**
Panel (d)—The effect of high-across on teammates						
High-across (0/1)	−0.062 (0.042)	−0.297 (0.098)	−0.056 (0.009)	−0.028 (0.011)	−0.008 (0.021)	−0.030 (0.006)
Within-team diversity	−0.008 (0.028)	0.016 (0.056)	0.038 (0.034)	−0.093 (0.033)	0.137 (0.029)	0.146 (0.023)
Constant	0.846 (0.338)	−2.004 (0.856)	0.339 (0.034)	0.685 (0.037)	0.260 (0.169)	0.283 (0.023)
Observations	42,134	20,971	20,971	20,971	21,003	20,975
Strata	493	472	472	472	388	449
R^2		.065	.036	.125		.059

Note: The CEM analysis categorizes the (a) external hire (Panels a and b) or (b) teammate (Panels c and d) sample into a treatment or control group, balanced in terms of pre-mobility characteristics (i.e., pre-mobility performance, R&D experience, and technological class), for each of the two treatment variables, *high-within* (Panels a and c) and *high-across* (Panels b and d). *High-within* (*high-across*) is a binary variable that take a value of 1 if *within-team diversity* (*across-team diversity*) value is above the median (0 if below the median). All models include firm-level characteristics and the diversity measure not used as a treatment variable (e.g., *across-team diversity* when the treatment effect is *high-within*) as control variables. The team diversity measures and controls are included as logged values for the models on number of patents (1), forward citations (2), and number of technological classes (5). All models include technology class and move year fixed effects. Robust *SE*s, clustered at the matched strata level, in parentheses.
Abbreviations: CEM, coarsened exact matching; OLS, ordinary least squares.

that the two groups have balanced pre-mobility characteristics based on the treatment variable. An advantage of CEM is that, as a non-parametric approach, it is less sensitive to model selection and the choice of a function for covariates. I analyzed the effects of two treatments—*high-within* and *high – across*, binary variables equal to "1" if the specific diversity measure is above the median (and "0" if below the median)—separately. For each treatment variable and for each external hire/teammate population, I used the following matching criteria: (a) pre-mobility 2-year performance used in each model depending on the outcome variable (e.g., pre-mobility *number of patents* if the outcome variable is post-mobility *number of patents*) split into quartiles; (b) *R&D experience* (by thresholds of 1, 3, 10, and 25); and (c) technological class (NBER subcategory). The CEM results, reported in Table 7, are broadly consistent with the main analyses. I show the standardized mean differences before and after the CEM procedure to demonstrate how it helps balance the pre-mobility subsamples in Appendix Table C4. Overall, the positive effects of *high – within* team diversity (Panels a and c) and the negative effects of *high – across* team diversity (Panels b and d) are persistent among both external hires (Panels a and b) and their teammates (Panels c and d).

5 | DISCUSSION

Management consulting reports and popular press articles highlight the ever-competitive war for talent in knowledge-intensive organizations (Burgess, 2018; Kaplan, Khan, & Roberts, 2012; Smith, 2018). One highly publicized example is Apple and Tesla poaching each other's employees. A report shows that Apple pays up to a 60% wage premium to recruit human capital from competitors (Higgins & Hull, 2015). The talent war is driven, at least in part, by accessing valuable external knowledge. In contrast to rising interest among practitioners on how to manage human capital resources, relatively little research has examined how firms can create an environment to maximize the benefits of external hiring. This article aims to shed light on this question by investigating an important firm characteristic—R&D team structure—that facilitates knowledge sharing and enhances the innovation capabilities of new hires and their teammates.

Based on my sample of U.S. patent inventors' mobility events, I find that external hires, on average, experience an improvement in innovation performance following a move. Yet I also discover an interesting trade-off in the quantity and quality of teammates' innovation performance. Teammates experience a reduction in productivity (i.e., number of inventions), but if they successfully create a patent, they create inventions with greater technological impact. Most importantly, I find that the post-mobility performances of external hires and their teammates are both contingent upon how teams are structured. Within-team diversity has a positive impact on innovation performance, while across-team diversity detracts from innovation performance. Assigning an existing employee to a team with an external hire who possesses a more distant knowledge background can mitigate productivity losses and improve the quality of inventions.

My findings contribute to different streams of research at the nexus of innovation and mobility. First, I highlight the importance of considering the effect of R&D team design on innovation. Organizational design shapes how its employees learn and absorb new knowledge (Clement & Puranam, 2018; Eklund & Kapoor, 2022; Karim & Kaul, 2015). In particular, understanding the critical role of collaborative teams in driving innovation within firms (Edmondson & Harvey, 2018; Mortensen & Haas, 2018; Singh & Fleming, 2010; Taylor & Greve, 2006; Teodoridis, 2018; Wuchty et al., 2007), scholars have explored how different ways of designing teams affect organization outcomes (Choudhury & Haas, 2018; Hoisl et al., 2017). Yet we know little about effectively assigning and integrating new hires into teams (Mawdsley & Somaya, 2016). Understanding how these different ways of structuring R&D teams affect the extent to which external hires and their collaborators contribute to the firm's innovation performance—a question overlooked by both the literature and many firms—could offer new insights. In search of finding the best R&D team design practices, I provide a more nuanced conceptualization of team knowledge diversity and its consequences for innovation performance. While prior investigations into team diversity have predominantly examined team diversity within a group or team, considering knowledge diversity between multiple teams is integral for maximizing knowledge sharing and productivity within a firm (Aggarwal et al., 2020; Hansen, 2002). The conceptualization of across-team diversity is particularly important because, in recent years, teams have become more fluid and dispersed with less clear boundaries (Mortensen & Haas, 2018). To the extent that individuals have agency over with whom to collaborate, the level of across-team diversity could represent the structure of future collaborative potential. Future research can further investigate the extent to which across-team diversity is associated with future collaborations between members from previously disparate teams, and how the fluidity of team structure is associated with innovation performance.

Another interesting avenue for future research is to examine how performance implications of R&D team design vary by firms' hiring and innovation strategies. To investigate a successful integration of the external hires into other members at the firm, I focus on the average role of R&D team design across different firms. Yet firms may differ in their hiring and innovation strategies, which may not be fully captured in the set of observable firm characteristics in my models. For example, firms differ in their preferences for hiring an individual who would complement or substitute the existing set of knowledge within a firm. The knowledge exchange production processes in teams may vary depending on whether firms are pursuing a radical or incremental innovation. As such, the extent to which R&D team design shapes post-mobility performances may vary according to these characteristics. Examining innovation and hiring strategy heterogeneities could help further validate the robustness of my estimates and also bring a more nuanced understanding of how team knowledge diversity shapes innovation processes and outcomes.

This study also contributes to research examining knowledge spillovers from mobility. While prior research on knowledge spillover has primarily focused on firm-level outcomes (Almeida & Kogut, 1999; Arrow, 1962; Rao & Drazin, 2002; Samila & Sorenson, 2011; Saxenian, 1994), I examine the process by observing individual performance contributions. I thereby distinguish the performance change of an external hire from how they contribute to their teammates' innovative capabilities. Moreover, my findings address a call from researchers to expand our knowledge on the process and extent to which the performance of teammates is affected after working with the hire (Mawdsley & Somaya, 2016). I find an interesting result that has not been documented in the literature: there is a trade-off in the quantity and quality of innovations by immediate collaborators. This study delineates the different ways in which external hiring is associated with the performance of a firm's broader human capital.

In addition, the findings have implications for research on human capital strategy. Scholars have shown inconsistent findings related to whether external hires experience performance gains (Hoisl, 2009; Tartari et al., 2020) or losses (Bidwell, 2011; Campbell et al., 2014; Groysberg et al., 2008; Raffiee & Byun, 2020), often described as the "portability of performance paradox." My findings suggest that focusing solely on the performance consequences of external hires to gauge value to firms may be a misspecified paradox. To evaluate whether external hiring is a value creating proposition for the firm, we also need to consider how external hiring is associated with the performance of other employees at the firm. Furthermore, results on team knowledge diversity suggest that external hires and their teams could experience performance losses due to ineffective team structure. In the worst-case scenario, external hires may leave a firm that does not offer an innovative environment. In fact, a supplementary analysis shows that a high level of within-team diversity is associated with longer tenure and reduced likelihood of departure within 2 years (Appendix Table C5). Thus, this article highlights the importance of jointly considering the ramifications of hiring and efficiently managing external talent.

Last but not least, my paper contributes to research on knowledge sharing across organizations (Botelho, 2018; Ingram & Roberts, 2000; Kogut & Zander, 1992; Spencer, 2003; von Hippel, 1987). Organization and strategy scholars find that promoting knowledge sharing not only within firms but also across firms, such as among competitors, improves firm outcomes. External hires, who are most likely to come from competitors engaging in similar technology, provide novel ideas that can be exchanged and built upon with new colleagues. In fact, I demonstrate that teammates use the new knowledge acquired from the hire and produce inventions with greater technological impact after working with new hires. This study illustrates that for knowledge sharing among team members within a firm to become valuable, sourcing different and diverse knowledge from other firms through external hires is critical.

Taken together, these findings have far-reaching implications for managers and employees. Many firms struggle to evaluate the value of external hiring. Specifically, existing research presents mixed evidence related to the performance of external hires at the new firm. Looking beyond the performance implications for focal hires, I explore how hiring is associated with the performance of other employees at the firm. Working with external hires decreases the productivity of immediate collaborators, but leads them to come up with more novel “breakthrough” innovations. Thus, managers should consider their immediate strategic or performance goals when devising recruiting strategies. For instance, firms trying to produce as many innovation outputs as possible during a short period of time would be better off forming teams with existing employees. Firms focused on creating breakthrough technology in a field should consider bringing in an external hire to enhance learning.

If a recruit has been hired, assigning them to collaborators with greater knowledge distance, rather than those who share a similar knowledge base, could lead to better collaborative performance. Furthermore, designing collaborative teams such that a high level of diversity exists within the team while allowing teams to diverge less from one another can create an environment that fosters innovative performance. Managers can adjust the composition of teams for better performance or, at a minimum, advise employees on how best to create teams with the optimal level of knowledge diversity.

This study also offers insights for employees considering a move to a different firm. From an employee's perspective, switching workplaces could bring both benefits (e.g., knowledge spillover) and costs (e.g., adjustment costs). Since post-mobility performance is contingent on team design, evaluating the organizational characteristics of the new firm and getting insights into their potential collaborators are important considerations for individuals to achieve their innovative potential.

Does external hiring constitute a value creating or value destroying proposition for firms? Although the patent data employed in this study offer many benefits, salary information is not included. While I explore how external hiring could bring knowledge benefits to firms, I could not directly assess whether or not these benefits offset the costs. Yet my results suggest that advantages from hiring accrue both directly from external hires and indirectly from knowledge spillovers to new teammates. The value and success of inventions follow a skewed distribution (Fleming, 2007). Thus, teammates with fewer but more novel and valuable patents may easily counterbalance the productivity loss of teammates and premium wages paid to external hires. The external hiring of star talent may therefore not be an irrational move by firms. Future research could compare how much a recruited inventor contributes to the firm and the associated costs of hiring by collecting compensation information. Nonetheless, this article highlights how external hires bring knowledge benefits to their teams and how to efficiently design teams to improve the *marginal benefits of external hiring*. External hiring, which enables knowledge sharing across firms, facilitates more lucrative knowledge sharing among incumbent employees within firms.

Overall, this research tackles an important challenge faced by managers in innovation-driven organizations: how to efficiently manage the talent pool through external hiring and designing R&D teams. Efficiently designing teams not only improves the innovation performance of external hires but can also enhance the learning benefits for their team members.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in PatentsView at https://patentsview.org/.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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