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Received: 2 July 2024 | Revised: 24 January 2026 | Accepted: 10 February 2026

DOI: 10.1002/smj.70076

RESEARCH ARTICLE

SMS | Strategic Management Journal WILEY

Hiring at the tip of the funnel: Externalizing the work of integrating and coordinating diverse human capital

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Abstract

Research Summary: We adopt a network-based perspective to examine the effects of hiring strategies in terms of the diversity of hiring sources. Considering the transferability of general and firm-specific skills, we propose that firms can reduce integration costs while gaining diversity benefits when they hire from a focused set of firms that themselves hire broadly. We suggest that occupying this position in the mobility network enhances both innovation and productivity outcomes. Moreover, we posit that a strong cultural orientation, characterized by high intensity and consistency, further amplifies these benefits. Our analysis of mobility data from US public firms between 2005 and 2021 uncovers the pathways through which firms attain this position. Evidence from the panel matching method and fixed-effects regressions provides support for our hypotheses.

Managerial Summary: We take a network perspective to understand how firms' hiring choices—particularly the range of companies they recruit from—shape their performance. We argue that firms can benefit when they hire from a small, consistent group of companies that themselves draw talent from many different firms. This approach allows firms to gain a wide variety of skills and experiences

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while keeping integration and onboarding challenges low, leading to more innovation and higher productivity. We also suggest that firms with a strong and consistent culture are even better positioned to take advantage of these benefits. Using data on employee movements among US public firms from 2005 to 2021, we show how firms attain this position, and find evidence in support of our hypotheses using panel matching and fixed effects models.

KEYWORDS

employee mobility, hiring, human capital, organizational culture, social networks

1 | INTRODUCTION

External hiring is an important means through which firms acquire valuable human capital which can form the basis of their competitive advantage (Barney, 1991; Coff, 1997; Hall, 1992; Wright et al., 2001). By tapping into the external talent pool, hiring firms gain access to the accumulated experiences and knowledge acquired from external hires' previous experience (Dokko et al., 2009; Song et al., 2003; Won & Bidwell, 2023). Consequently, the question of "where to hire from" has garnered significant attention among scholars (Gardner, 2002; Keller et al., 2021; Tan & Rider, 2017), especially given the increasing trend of recruiting experienced workers (Cappelli, 1999). Existing research on external hiring has predominantly examined individual transitions between two organizations (for a review, see Mawdsley & Somaya, 2016), with few studies that focused on team mobility (e.g., Campbell et al., 2014; Groysberg et al., 2008) and cluster hiring (e.g., Eckardt et al., 2018). However, given that the composition of the workforce matters (Reskin et al., 1999), we can also expect that the collective characteristics of an *entire* incoming workforce could substantially influence the recipient organization's capabilities (Tomaskovic-Devey, 2013). This broader perspective raises a critical question that remains underexplored in prior literature: does hiring from many organizations confer greater benefits than recruiting from a more focused set of organizations? On the one hand, hiring from many may offer the hiring organization access to a wide array of perspectives and diverse sets of knowledge (Corredoira & Rosenkopf, 2010). On the other hand, it may present challenges in coordinating individuals with varying sets of norms and working styles, potentially complicating the integration and adaptation process (Cox, 1994).

Our answer to this question is neither "hire from somewhere between many and few" (suggesting a curvilinear relationship) nor "it depends" (suggesting moderators that shape the direction of the effect). Instead, we adopt a network perspective (McDonald & Benton, 2017; Tomaskovic-Devey, 2013; Wilcox et al., 2022) to propose a novel solution where firms can benefit from the diverse past affiliations of new hires *and* circumvent the inherent integration challenges. Specifically, we propose that firms can benefit from an advantageous network position that we term "the tip of the funnel," which refers to the hiring strategy characterized by sourcing from other firms that hire broadly, but only hire from a few such firms. We suggest that this position effectively allows the hiring firms to externalize the effort of integrating and coordinating diverse human capital to the firms they hire from.

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Adopting the network perspective not only allows us to investigate the composition of the incoming workforce; it also facilitates the examination of indirect ties within the mobility network (Burt, 2007; Galunic et al., 2012). Existing literature has primarily focused on the organizations they hire directly from (i.e., the alters within the first order in the mobility network). Yet it is important to consider that the knowledge flowing into the hiring firm through new hires is not limited to that which originated from the source firm; it also includes the knowledge that the source firm itself has acquired and integrated from other firms through external hires. This broader perspective necessitates an examination of the entire mobility network by situating each organization within a vast network of all moves between organizations and considering indirect as well as direct ties between organizations.

To examine the flow of human capital from both directly and indirectly connected firms within the mobility network, we distinguish between the inter-firm transferability of general versus firm-specific human capital. While research on human capital portability has traditionally focused on individual-level transfers between two firms (e.g., Groysberg et al., 2008), these dynamics also have significant implications for human capital flow across multiple organizations. By examining two key organizational processes at the source firm—which we will call the *mediating firm*—that shape the human capital flow, we analyze the costs and benefits of occupying different positions within the mobility network.

First, general human capital is highly transferable across firms (Becker, 1962). When the mediating firm hires externally, new hires bring their general human capital with them. The firm then absorbs and integrates this knowledge with its existing knowledge base, which is subsequently transferred throughout the organization for utilization. When a focal firm recruits from the mediating firm, it can access the integrated knowledge through its new hire. This suggests that general human capital can travel through organizations, beyond those that are connected through direct mobility ties. Assuming each firm holds a heterogeneous knowledge base (Barney, 1991), hiring from a broad set of firms increases the diversity of the firm's human capital. Hiring from a mediating firm that hires broadly will then increase the diversity of the human capital for the focal firm.

Second, we examine the socialization process at the mediating firm. Organizations require effective coordination to utilize human capital, which is often achieved by acculturating new employees to organizational norms (Bauer et al., 2007; Van Maanen & Schein, 1979). Since cultural norms, communication styles, and working practices from previous employment can create integration costs at the new firm (Dokko et al., 2009), hiring firms must dissolve and replace old norms through socialization processes (Bartunek & Moch, 1987). Consequently, human capital related to organizational norms only transfers from directly connected alters; therefore, the focal firm needs to address only the cultural norms formed at the mediating firm. Given that firms hold unique organizational cultures, greater socialization efforts are required when hiring from multiple organizations rather than a few. Thus, firms can reduce coordination costs by hiring from a focused group of mediating firms.

Taking these together, we propose that firms at the "tip of the funnel" within the mobility network (Bothner et al., 2010) that hire from a focused set of firms that themselves hire from a diverse set of firms will achieve superior performance in terms of innovation as well as productivity.

We also explore the conditions under which the tip-of-the-funnel position can be best leveraged to achieve favorable organizational outcomes. A key focus is on organizational culture (Chatman & O'Reilly, 2016), crucial for integrating and leveraging human capital within a company. We build on the recent literature that distinguishes three foundational elements of

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organizational culture (Chatman et al., 2014): cultural consensus, norm intensity, and norm content. By incorporating a novel dimension of time, we suggest that organizations with strong organizational culture—characterized by intensity and consistency—and those with norm content aligned with the firm's goal are more likely to reap the benefits of occupying the ideal network position.

We test these ideas in the context of mobility across public firms in the United States from 2005 to 2021 by examining the network positions of the organizations. To develop our empirical strategy, we first explore the mechanism through which firms achieve the desirable network position. Sequence analysis revealed that firms reach the tip-of-the-funnel position by hiring from a focused set of firms that either have or later adopt a broad hiring strategy. Additionally, high-performing and reputable firms were more likely to occupy these positions.

By using the panel matching approach, we found that occupying the tip-of-the-funnel position was associated with higher performance in terms of patent intensity and total factor productivity compared to other positions. To examine the moderating effect of culture, we developed a time-varying measure of different dimensions of organizational culture using Concept Mover's Distance (CMD) and found that the more intense and consistent the organizational culture, the more salient the impact of the tip-of-the-funnel position is on the firm's performance, especially on the dimensions that align with the organizational culture.

This paper makes important contributions to the field. First, it introduces a novel, network-based framework to study hiring strategy, moving beyond past studies that focused on individual transitions across organizations and dyadic relationships between organizations. Through this approach, we find more nuanced results around the transferability of different types of human capital, as well as identifying an advantageous network position that can drive important firm-level outcomes. Second, within the context of hiring, we highlight the significant role of the organizational culture in enabling organizations to leverage a favorable network position. Third, we also add to the literature on diversity by suggesting an important dimension—past organizational membership—that can shape critical organizational outcomes.

2 | THEORY AND HYPOTHESES

2.1 | Where to hire from? Examining the source of external hiring

Extant research has extensively documented the strategic implications of external hiring, a critical process through which organizations acquire talent. This perspective aligns with the resource-based view of firms, which suggests that human capital is a vital resource from which firms can derive competitive advantage (Barney, 1991; Coff, 1997; Wright et al., 2001). The acquisition of talent, therefore, becomes an important activity for shaping a firm's human capital pool and ultimately its performance.

Consequently, researchers have examined the effectiveness of various recruitment practices. One of the key areas of focus has been the *source* of hire, as new hires bring valuable human capital from their prior employment (Almeida & Kogut, 1999; Song et al., 2003). Hiring from distant firms, for example, can introduce more novel knowledge into the organization (Rosenkopf & Almeida, 2003). Bidwell and Briscoe (2010) highlight how smaller firms may benefit from hiring employees from larger organizations, which often provide more robust training. Employee mobility can also facilitate the transfer of social capital. For instance, hiring from competitors can help firms gain more business from the clients of the competitor (Somaya

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et al., 2008). Additionally, hiring from high-status firms can enhance a firm's legitimacy and status (Rider & Tan, 2015).

This body of research has predominantly paid attention to individual hires, examining the attributes of each new hire's prior affiliation. Yet it is also important to consider the composition and structure of the entire incoming workforce, as it opens doors to new research questions. Within the context of external hiring, few studies examined team mobility and cluster hiring and further identified dynamics that can arise when considering a group of new hires, such as leveraging relational capital within teams (Campbell et al., 2014; Groysberg et al., 2008) or enabling appropriation or integration (Eckardt et al., 2018). Past studies have also documented the impact of workforce composition on various outcomes, such as turnover and organizational performance (Reskin et al., 1999). Therefore, it is reasonable to anticipate that the composition and structure of the entire incoming workforce also have the potential to influence the organization's capabilities, leading to important organizational outcomes such as innovation, adaptability, and overall performance (Lazear, 1999; Sheridan, 1992; Tomaskovic-Devey, 2013).

2.2 | Adopting a network perspective to examine external hiring

To examine the composition of the incoming workforce in terms of their prior affiliations, we adopt a network perspective and situate firms within the mobility network where each move from one firm to another constitutes a tie between two firms, wherein these ties serve as conduits for information, knowledge, and skills transfer. Using this perspective, several studies have shed light on various implications of these mobility-induced ties. Notably, Godart et al. (2014) documented the effects of outward centrality—that is, the range of employers that employees from the focal firm move to—particularly on organizational creativity. Tan and Rider (2017) demonstrated that increasing rates of career-advancing employee departures to competitors can enhance a firm's status in the labor market.

In this paper, we leverage two unique advantages of adopting a network perspective to explore the benefits and challenges of occupying different positions within the mobility network: first, it enables a comprehensive analysis of the incoming workforce's composition in terms of their prior affiliations. Second, it aids in conceptualizing the flow of human capital through both direct (firms that the focal firm directly hires from, i.e., the source firms) and indirect (firms that the source firms hire from) ties (Burt, 2007; Galunic et al., 2012).[1]

2.3 | The role of the mediating firm and the flow of human capital within the mobility network

We next evaluate the role of the mediating firms—the source firms of the focal firm—which shapes the flow of human capital within the mobility network, and the implication it has for

[1]Few studies in the network literature have explored the effect of indirect ties, such as research on second-hand brokerage or social capital (Burt, 2007; Galunic et al., 2012; Shah et al., 2018) in the context of workforce mobility. However, they evaluated the direct and indirect effects separately and did not examine the possible interaction effects. In addition, those studies were conducted in cross-sectional and organization-specific settings, which makes it challenging to identify causal effects and to generalize their results.

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the benefits and challenges of occupying various structural positions. We consider the two processes that take place at the mediating firm: (1) the knowledge acquisition and integration and (2) the socialization process.

2.3.1 | Knowledge acquisition and integration process and the flow of general human capital

We first examine the knowledge acquisition process to delineate how general human capital can be transferred through multiple organizations. We can conceptualize the process from a firm's perspective as a recurring cycle of knowledge absorption, integration, and transfer among organizational members. When a firm hires an employee from another organization, the newcomer brings with them some human capital from their prior employer (Song et al., 2003). Of particular interest is general human capital, which is broadly applicable across firms, industries, and roles (Becker, 1962; Groysberg, 2010). This hiring marks the absorption phase of the cycle. Next, the firm integrates the incoming knowledge with its existing knowledge base to enhance its value (Nagle & Teodoridis, 2020; Zhou & Li, 2012). The integrated knowledge is then transferred to other employees through both formal mechanisms, such as training programs, and informal interactions (Kale & Singh, 2007; Verona, 1999). When employees subsequently leave, they carry with them the accumulated, integrated knowledge, thereby transferring it to their next employer. This movement continues the ongoing cycle of knowledge absorption, integration, and transfer.

This process has two implications for organizations within the mobility network. First, hiring from a diverse set of firms will enhance the diversity of human capital integrated into the hiring firm. Given that each company develops its unique reservoir of knowledge base (Barney, 1991), such a hiring strategy offers the potential to infuse the organization with a rich mix of skills, experiences, and perspectives (Jackson & Schuler, 1995), which can serve as a catalyst for innovation and creativity. It can also enhance the organization's adaptability in rapidly changing markets, as employees with diverse experiences may be better equipped to identify and respond to emerging trends and challenges (Sheremata, 2000).

Second, the benefits of this diverse human capital will extend beyond the firms that directly hire from broad sources. Firms that subsequently hire individuals from these broadly-sourcing organizations will also benefit indirectly, since the new hires will bring with them the diverse human capital they have acquired in their previous organization.

2.3.2 | Socialization process and the flow of firm-specific liabilities within the mobility network

An important process that follows recruitment is a socialization process, which helps the organization leverage new hires' human capital more effectively. It includes orientation, training, mentoring, and gradual integration into the company culture and work systems (Bauer et al., 2007; Feldman, 1981). Firms use such processes to help new employees adapt to their roles, understand company values and expectations, build relationships with colleagues, and become productive team members more quickly. As new employees become socialized into the environment, they learn unique habits, routines, and other cognitions, which allows them to perform more effectively within the organization (Adkins, 1995; Beyer & Hannah, 2002). Van

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Maanen and Schein (1979) state that: "socialization entails the learning of a cultural perspective that can be brought to bear on both commonplace and unusual matters going on in the workplace [...] a perspective for interpreting one's experiences in a given sphere of the work world."

This tacit knowledge has been understood as a type of firm-specific human capital (Becker, 1964; Lepak & Snell, 1999), as it is deeply ingrained in the context, processes, and culture of specific organizations. Even within the same industry or occupation, individuals may learn different sets of norms and cognitive schemas from different organizations, which will guide their behavior at work (Dokko et al., 2009). While highly valuable within the organization where it was developed, its value within a new environment is limited, which is a key feature of firm-specific human capital.

Although firm-specific human capital is generally conceived as having no value in a new organization, we posit that those elements that employees have acquired during the socialization process—such as communication styles, cultural norms, and expectations—can generate *negative* value and pose integration challenges at the new firm. These deeply ingrained behavioral patterns and assumptions from previous employers may clash with the new organization's culture and impede their performance. Studies have documented how they can hinder the adaptation process when applied in a different context by creating rigidities, "weighing down their responsiveness or ability to reflect in the new situation" (Dokko et al., 2009, p. 54). Hence, the accumulation of such firm-specific human capital from previous employment may become a liability for the hiring firm. It is likely to undermine performance (Dokko et al., 2009) and could negatively affect the performance of others, especially if their tasks are interdependent. A study by Won and Bidwell (2023) documents the concern among employers regarding adaptability when a job candidate has remained with their current employer for an extended period. In their study, the concern that "[the new hire] would struggle to adapt to working in a different organization and learning a new culture" (p. 24) ranked highest among employers' various considerations.

When hiring from other organizations, firms must therefore replace employees' existing schemas during the socialization process (Bartunek & Moch, 1987; Van Maanen & Schein, 1979). Through adaptation and socialization, new hires acquire a new set of habits, routines and cognitions, aligning their behavior with the new employer's practices, norms, and values (Bauer et al., 2007; Feldman, 1981). Due to this replacement process, the cultural norms and expectations carried over from one's most recent employment—namely, directly connected firms from the perspective of the hiring firm—will be particularly relevant.

Taking these together, we can expect that hiring from multiple firms may create more integration challenges for the hiring firm because of the various firm-specific baggage that new hires bring. The process of harmonizing these varied habits and cognitions can be complex and resource-intensive, leading to communication barriers, misaligned work practices, or conflicts in corporate values (Chatman & Flynn, 2001; Lau & Murnighan, 1998).

If a firm instead hires from a focused set of firms, it may facilitate a quicker and more efficient integration of the new employees. This approach can lead to quicker adaptation, reduced training and onboarding times, and faster attainment of full productivity. Additionally, as Brymer et al. (2019) note, by relying on a few sources repeatedly, organizations can reduce information asymmetry and learn to find and develop fit with the new hires.

Combining these arguments on the human capital integration and coordination strategies and the flow of general human capital and firm-specific liabilities, we propose that an optimal strategy is to hire from a focused set of firms that themselves hire from a broad set of firms (as depicted in a bottom-right cell in Figure 1). Firms that hire from the "tip of the funnel" can

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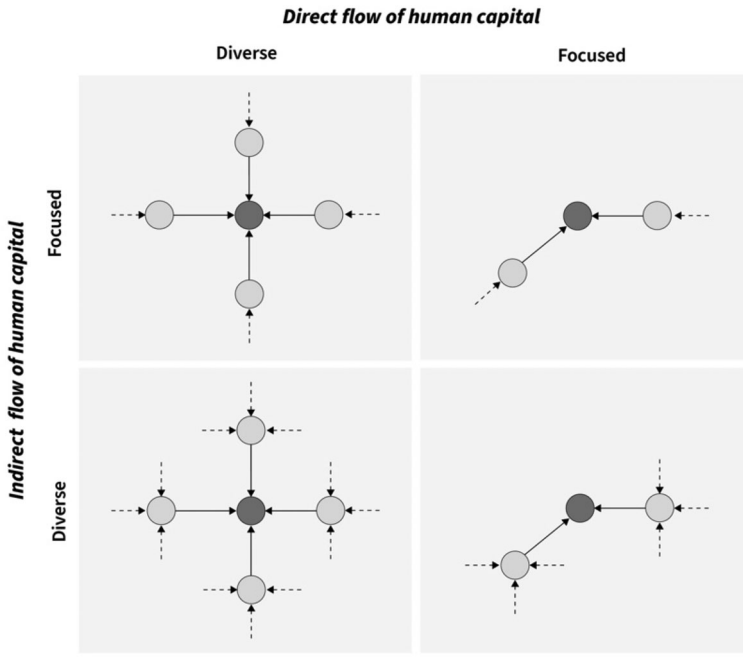


FIGURE 1 Hiring firms' position within the mobility network. The dark circle signifies the focal firm, and the lighter circle represents the firms that the focal firm hires from. Solid line denotes the direct inflow of human capital from the most recent employer of each new hire. Dotted line represents the inflow of human capital into the prior employers of the new hires.

externalize the complexity and costs associated with coordinating employees from various organizational backgrounds to the mediating firm, thus streamlining the adaptation process. At the same time, they can acquire diverse human capital that the mediating firm has accumulated from a wide range of firms which will be conducive to superior innovation outcomes. Hence, we hypothesize that:

> **Hypothesis 1a.** Hiring from a set of focused companies that themselves hire broadly will be associated with a higher level of performance related to innovation compared to hiring broadly or hiring from a focused set of firms that themselves do not hire broadly.

There are reasons to believe that occupying the tip-of-the-funnel position can also lead to productivity improvements. The extant literature on lean systems, for example, emphasizes the importance of idea generation in continually improving processes and operations (Murman et al., 2016). By drawing from a broad knowledge base of new hires, firms can benefit from a wider range of ideas, which can be utilized in their idea-generation processes to find solutions that make their operations more efficient. Indeed, research examining various dimensions of diversity supports these productivity benefits (Gomez & Bernet, 2019; Kunze et al., 2013; Lazear, 1999). Therefore, we expect the aforementioned relationship to also hold for performance related to productivity:

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Hypothesis 1b. Hiring from a set of focused companies that themselves hire broadly will be associated with a higher level of performance related to productivity compared to hiring broadly or hiring from a focused set of firms that themselves do not hire broadly.

2.4 | Content and strength of organizational culture

We proposed that occupying the tip-of-the-funnel position can lead to superior innovation and productivity outcomes. In doing so, we assume that firms have practices, norms, and values conducive to achieving their organizational goals, to which new hires can be socialized. However, without a strong cultural orientation that supports their goals, firms may not fully benefit from occupying this advantageous network position. We posit that the benefit of this strategic positioning will be contingent on the organization's cultural orientation and its strength.

Organizational researchers have long been interested in the role of culture in organizations and how organizational culture constrains or enables the focal organization's behavior and performance. In particular, we draw from and build on the work by Chatman et al. (2014) on the content and strength of culture. First, the content of the organizational culture determines the alignment between the values that are espoused by the culture and the organizational goals. For example, we can consider that there is a high level of alignment when an organization that seeks to achieve superior innovation outcomes cultivates a culture that emphasizes values such as creativity and diversity.

Second, the strength of the organizational culture affects the alignment of individuals to the organizational culture (Burt et al., 1994; Chatman et al., 2014; Kotter & Heskett, 1992; Marchetti & Puranam, 2022; Sørensen, 2002). Research suggests that a strong organizational culture cultivates a unified vision, increased employee engagement, improved communication, or clear expectations (Burt et al., 1994; Chatman et al., 2014; Kotter & Heskett, 1992; Marchetti & Puranam, 2022). In the context of external hiring, a strong culture provides a clear blueprint of the cultural orientation the new hires must assume, for the new hires as well as the incumbents who will assist in the process. This will help the integration process to proceed more efficiently and effectively, aligning individual employees' cognition and behaviors with organizational strategic priorities. While previous research has mainly focused on the intensity of organizational culture, we conceptualize the strength of organizational culture in two ways: intensity and consistency. Intensity refers to the strength or pervasiveness of an organization's culture; that is, how deeply the cultural values are held by members of the organization. In contrast, consistency indicates the degree of consistency of the culture over time. This view extends the existing studies on organizational culture (Chatman et al., 2014) by incorporating a temporal dimension. Given the variation in how enduring organizational cultures are in practice, it is important to consider how organizational culture is sustained across multiple points in time. If an organization's culture exhibits high intensity at one point in time but is highly volatile over time, it may not be considered a strong culture.

Considering both the content and strength of organizational culture is akin to viewing it as a "vector," where direction captures content and its alignment with organizational goals, and magnitude reflects strength. For a firm to benefit from the tip-of-the-funnel position, we suggest that both alignment and strength are important. Therefore, we hypothesize as follows:

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Hypothesis 2a. The association between hiring from a set of focused companies that themselves hire broadly and innovation outcomes will be stronger within firms with a strong, diverse and innovation-oriented culture.

Hypothesis 2b. The association between hiring from a set of focused companies that themselves hire broadly and productivity will be stronger within firms with a strong collective and efficiency-oriented culture.

3 | DATA AND METHODS

We test our hypotheses using a set of publicly traded US companies from 2005 through 2021. For our study, we used five distinct data sources. First, we employ data from Revelio Labs—a workforce intelligence company that gathers employment information of workers from various websites and social media platforms such as LinkedIn. The raw data include more than 380 million online profiles regarding individual's current and historical positions, educational histories, and demographic information. We used this data to construct the mobility network and the related measures.[2]

Second, we used Standard & Poor's Compustat Fundamentals Annual and Segments data to collect a broad range of financial measures that we use as control variables. Third, we used Center for the Study of Security Prices (CRSP) data to calculate the firm-level productivity. Fourth, we used the UVA Darden Global Corporate Patent Dataset to merge firm-level annual patent counts. The dataset covers patents awarded by the US Patent and Trademark Office (USPTO) to international publicly listed firms covered by the S&P Compustat Global database.

Finally, we collected the employee review data from Glassdoor to measure organizational culture. Glassdoor offers the most comprehensive set of employee reviews in terms of both firm coverage and information content from approximately one million employers (Chi & Chen, 2021), and recent studies on organizational culture have increasingly taken advantage of Glassdoor data to operationalize cultural aspects of organizations (Corritore et al., 2020). We web-crawled the entire set of employee reviews for our sample firms deposited on the Glassdoor website as of January 2024 and also extracted other evaluation scores such as company overall ratings. Since Glassdoor reviews are only available from 2008 onward, missing values in earlier years were imputed through linear interpolation and limited extrapolation within each firm.[3] Our final sample consists of 23,156 firm-year observations across 2403 firms.

[2]One caveat of the data is that white-collar occupations tend to be the largest represented group in the data (Li et al., 2022), which is a common issue in studies that utilize data sourced from LinkedIn and similar platforms. A wide range of occupation is better represented for companies with higher visibility such as public companies listed in major stock markets in the U.S. like NYSE, NASDAQ, or AMEX. One recent study examined the reliability of online source data including LinkedIn in terms of workforce demographic composition by race, ethnicity, and gender, and found that those online data sources provide reasonably reliable measures (Berry et al., 2024).

[3]This approach assumes that organizational culture evolves gradually over time and that short-term extrapolation provides a reasonable approximation of pre-observation values. We conducted a robustness check by restricting our sample to the period during which the Glassdoor review data are more reliable and representative, from 2009 onward. We re-estimated all models using the 2009–2021 sample and found qualitatively similar results.

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3.1 | How do firms occupy the tip-of-the-funnel position?

While our theory treats firms' occupation of positions within the mobility network as given, it is important to understand how firms attain tip-of-the-funnel positions and which firms do so.

Since the network position that we study in this paper considers both direct and indirect ties, a firm's ability to occupy a desirable position stems from both its own hiring decisions and the actions of other firms. That is, it depends on the hiring strategy of the focal firm as well as those of the source firms (alters).

We consider two possible paths to reaching the tip-of-the-funnel position. The first path begins with firms hiring from a diverse set of source firms, where most firms occupy the direct diverse-indirect diverse position (maximally diverse, as depicted in the bottom-left picture of Figure 1). Over time, the focal firm may develop a preference for hiring from a small set of firms among the subset of these source firms, eventually leading to a culling process and moving to a direct focused-indirect diverse position (shown in the bottom-right of Figure 1), which represents the tip-of-the-funnel position.

The second possible path is a transition from direct focused-indirect focused to a direct focused-indirect diverse position. Starting with the direct ties, we can expect that firms may generally prefer to hire from a select pool of source firms. While there may be benefits to hiring from a variety of firms, this advantage might not always be evident to the hiring firms, who may have specific preferences for certain companies. For instance, firms typically favor candidates from high-status companies (Rider & Tan, 2015). Certain firms may be recognized for hiring and training high-quality workers, so other firms may prefer to hire from them. Once firms successfully hire from a select group of desired sources, they are likely to continue doing so due to reduced uncertainty for both the hiring firm and the potential applicants. Employees may also encourage individuals from prior employers to join their organizations (Campero & Kacperczyk, 2024). While most firms may seek to hire from select sources, not all may be able to do so. Those less desirable in the labor market may need to fill positions from a broader array of source firms that are not their top choice, while their reputable counterparts may use a focused hiring strategy. Next, we consider the configuration of indirect ties, which reflects the hiring strategy of the hiring sources (alters). A firm that is able to source from a select group of firms might begin hiring from alters with either focused or broad hiring strategies. Given that a focal firm may have limited knowledge of its alters' hiring strategies, some firms may find themselves randomly placed into the tip-of-the-funnel position (alter hires broadly), while others may occupy a focused-focused position (top-right picture from Figure 1 below; alter hires selectively). For these latter firms, the path to achieving the tip-of-the-funnel position involves the alters switching to a more diverse hiring strategy. Although one might observe a similar pattern of results if the focal firm has switched their sources rather than the source firms altering their strategies, we consider it less likely given the persistence of the hiring strategies discussed earlier.

To investigate these possibilities, we used a sequence analysis (Abbott, 1995; Cornwell, 2015) to explore the common path through which firms achieve the tip-of-the-funnel position. The analysis began by categorizing firms' annual direct inflow concentrations into three equal tiers (high, medium, and low), with each tier containing one-third of the firms. Each company was then assigned a specific combination of direct and indirect concentrations for each year (e.g., "high-low" to represent high direct concentration and low indirect concentration), reflecting its positioning across both dimensions. To ensure data reliability and

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consistency, only firms with at least 10 consecutive years of complete data[4]—free from missing values for both direct and indirect concentration measures—were included. For this subset of firms, the most recent 10-year sequences were selected for further examination. This process yielded a dataset comprising 1640 firms that satisfied the criteria. Next, we used sequence analysis to uncover the most representative patterns across firms. Ten distinct and illustrative sequences were identified, highlighting prevalent pathways by which firms achieve various network positions over time.[5] Sequence types, along with the frequencies, are reported in Figure A1 of the Appendix. We see that firms in the tip-of-the-funnel position had most commonly transitioned from a focused-focused (top-right) position (Sequence 9 in Figure A1). This aligns with the second scenario, where certain firms achieve the initial step of hiring selectively from a focused set of firms before reaching the tip-of-the-funnel position. We exploit the fact that some firms inadvertently attain this position due to changes in their alters' hiring strategies and use this as our identification strategy within a panel matching approach, described in detail in the next section.

We conducted additional analyses to investigate the factors influencing the likelihood of using a focused strategy as well as the likelihood of occupying the tip-of-the-funnel position. First, we checked which firms are more likely to use a focused hiring strategy (i.e., have a high direct concentration score) by using the level of direct inflow concentration as the dependent variable. The results are reported in Table A1 of the Appendix. We found that large, high-status firms typically adopt a focused hiring strategy, as evidenced by the positive coefficients on *the number of employees* and *inflow centrality*. This is consistent with our expectation that reputable firms hire from a few preferred source firms. Next, to estimate the likelihood of occupying the tip-of-the-funnel position, we used the panel multinomial logistic regression. We categorized the annual levels of direct and indirect inflow concentrations for all firms into two tiers—high and low.[6] The model incorporates two-way fixed effects to account for unobserved time-invariant confounders. Table A2 of the Appendix presents the coefficient estimates for the three types of network positions, interpreted relative to the baseline category (Concentrated-Diverse, or the "tip of the funnel"). We find that the relative likelihood of occupying the tip-of-the-funnel position increases with firm size (measured as the log of assets) and inflow-based centrality, a measure of firm status. Additionally, firms listed in the Fortune 100 are more likely to occupy the tip-of-the-funnel position.

Hence for our analysis, it is important to control for measures related to the attractiveness of the firm, such as its reputation in the labor market and overall performance. We describe in more detail the variables that we use in our analyses below.

3.2 | Analytical models

Panel matching method: We build on our earlier finding from the data-generating process, which showed that the most common path to attaining the tip-of-the-funnel position occurs when a firm previously hiring from a narrow set of firms finds that its alters broaden their hiring strategies—a change beyond the focal firm's control. This dynamic exemplifies what

[4]Using different lengths for consecutive years, such as 15 years, yielded similar results.

[5]Varying the number of sequence clusters, such as increasing it to 15 or 20, produced consistent results.

[6]This simplified categorization differs from the previous scheme used for the sequence analysis, as an increasing number of categories complicates the reliable estimation of multinomial logistic regression.

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Hernandez et al. (2025) describe as *other-driven* network position changes, which are particularly valuable for causal identification because they arise independently of the focal firm's actions. In our analysis, we apply the panel matching method of Imai et al. (2023) to isolate other-driven changes that enable firms to attain advantageous network positions.

In our context, firms exercise agency over their direct ties through their choice of source firms but not over the hiring behaviors of those sources. Thus, variation in direct inflow concentration reflects self-driven changes, whereas variation in indirect inflow concentration reflects other-driven changes. We treat the latter as an exogenous source of variation that allows us to identify the causal effect of network position.

We categorized the indirect inflow concentration levels into three tiers: high, mid, and low, with cutoffs at the 33% and 67% percentiles. We defined "low" indirect inflow concentration as the treatment condition—that is, when the source firms hire from a broader range of sources. We then matched firms on covariate profiles as well as their treatment histories.[7] The matched firms are equivalent in terms of all covariates, except for the treatment at time *t*. Depending on the direct concentration level, treated firms may end up in either of the two positions at time *t*: (1) the tip-of-the-funnel position if they are using a focused hiring strategy (high direct concentration) or (2) a maximally diverse position (direct diverse-indirect diverse) if they are using a diverse hiring strategy (low direct concentration).

Therefore, we can assess the effect of the tip-of-the-funnel position on firm outcomes by estimating the treatment effect for those that employed a focused hiring strategy. We do so by estimating an interaction term between the treatment variable and a variable representing direct inflow concentration (binary; high vs. mid/low).

Fixed effects models: To establish baseline results for H1a and H1b and to test H2a and H2b, we employed firm- and year-fixed effects models to account for unobserved, time-invariant heterogeneity across firms, using Huber–White robust standard errors.

To test H1a and H1b, we used the same set of variables across the panel matching and fixed-effects models. Variables included as covariate profiles for matching in the panel matching method were used as control variables in the fixed-effects model.

3.3 | Dependent variables

Patent intensity: We utilized the ratio of firm-level patent counts granted in a given year to its assets to measure its patenting intensity (Frésard et al., 2020). The measure normalizes the number of patents with the total assets, allowing for meaningful comparisons across firms of different scales. We focus on patents awarded by grant year rather than application year because we seek to capture the success of innovation activities. Given that the average time for getting a patent in the United States is around 2 years according to the USPTO, we lagged this variable by 2 years.

[7]In order to construct the matched sample sets, we used covariate balancing propensity score (CBPS) weights for matching refinement, set the number of controls matched to each treated unit as two, and included all the independent and control variables used in main analysis, with two-year lags for defining the similarities between observations. For calculating the standard errors, we used the block bootstrap procedure while accounting for both dependencies arising across units and across time. In general, the matched qualities across those refinement covariates are excellent given that the standardized mean difference for all the covariates included is less than 0.1. The plots for covariate balance and balance scatter patterns are available upon request.

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Total factor productivity: We capture performance related to productivity using firm-level total factor productivity (TFP). We adopted the semiparametric method by İmrohoroğlu and Tüzel (2014) to estimate the firm-level TFP as the main dependent variable, which measures the overall effectiveness with which capital and labor are used in a production process. İmrohoroğlu and Tüzel's TFP measure provides a broader gauge of firm-level performance than some of the more conventional measures such as labor productivity or firm profitability. The production function is as follows:

$$y_{it} = \beta_0 + \beta_{1k} k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it},$$

where y_{it} is the log of value added for firm i in period t; l_{it} and k_{it} are log values of labor and capital of the firm, respectively; ω_{it} is the productivity; and η_{it} is an error term. They employ the semiparametric procedure and the major advantage of this approach over other traditional estimation techniques is its ability to control for selection and simultaneity biases and address the within-firm serial correlation in productivity (İmrohoroğlu & Tüzel, 2014).

Once the production function parameters are estimated with industry-specific time dummies, we obtain the firm-level (log) TFPs as follows:

$$\omega_{it} = y_{it} - \widehat{\beta}_0 - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it}.$$

3.4 | Independent variables

Direct inflow concentration score: To measure the concentration score, we first aggregated the individual-level data at the dyadic firm-to-firm level to produce the inflow and outflow mobility flow data. While we focus on the new hires (inflow) in our theorization, we also constructed measures related to turnover (outflow) to include them as control variables. We calculated the number of employees who entered or left a specific firm for another firm in a particular year and aggregated the dyadic firm-to-firm level data on the inflow and outflow volume into direct and indirect concentration scores. Specifically, we measured the degree to which firm-level employees' inflow and outflow are diverse or focused, building on the network-based measure suggested by Bothner et al. (2010).[8] First, the Herfindahl index for firm i is expressed as:

$$H_i = \sum_{j=1}^{n-1} d_{ij},$$

where x_{ij} denotes the level of employees' mobility flows directed from firm j to i, and d_{ij} equals:

[8]Within the context of supplier–buyer relationships, Bothner et al. (2010) introduced the robust positions as ones with diversified support from durably located others and the fragile positions as dependents on tenuously situated others. They extended the existing Herfindahl's index of concentration by bringing in the recursiveness of Bonacich's (1987) measure of status or centrality. We follow this approach in this paper but depart from their work by distinguishing between the first-order (direct) and the second-order (indirect) network fragilities.

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$$d_{ij} = \left[\frac{x_{ij}}{\sum_{j=1}^{n-1} x_{ij}} \right]^2 .$$

If H_i equals one, it indicates that firm i receives all new hires from just one firm in the network. Hence firm i's hiring strategy is regarded as maximally concentrated. In the opposite scenario, where the index for a given firm equals $1/(n-1)$, the firm's hiring strategy is minimally concentrated, as they hire from nearly an infinite number of other firms. We calculated the direct inflow concentration scores for each firm for each year.

Indirect inflow concentration scores: We also generated the indirect concentration scores by calculating the average of alters' direct inflow concentration scores for each year.

Organizational cultural dimensions: To capture organizational culture, we applied the word embeddings and concept mover's distance (CMD) to the corpus of employee review texts from Glassdoor (Stoltz & Taylor, 2024). Word embeddings represent relationships between words in texts in a vector form such that the positions of words in the word embedding space are determined based on their relationships with the other words in the context. Terms that frequently appear near the word of interest in the corpus are thus represented close to that word in the vector space, whereas words that rarely appear with the word of interest are represented far from that word. Accordingly, the relative positions of words in the vector space can hint at their semantic meaning (Bolukbasi et al., 2016; Caliskan et al., 2017). For instance, words semantically closer to "diverse" will be located closer to the cluster of words related to "diverse" in the word embedding space.

CMD allows us to find the extent to which an employee review text is close to one prototypical concept in the word embedding space (Stoltz & Taylor, 2024). To measure this, for each review, we used CMD to calculate an optimal distance between the words from the employee reviews and the "ideal" pseudo-document consisting of only words denoting one specific concept.

As CMD is deductive in nature, we must select which pairs of words to use as concept words for prototypical concepts. For our study, we decided to evaluate four important cultural dimensions of organizations by using a set of concept words that denote the concepts of (1) collectiveness, (2) efficiency, (3) diversity, and (4) innovation as shown in Table A3 of the Appendix. After that, the location of each dimension is calculated as the average of optimal distances between the words in the employee review and each dimensional vector that represents the prototypical concept. This creates a one-dimensional continuum where employee reviews that are closer to a specific cultural dimension indicate a greater emphasis on that dimension, while reviews farther away suggest less emphasis. We then aggregated this index across all reviews that belong to each firm for each year. Therefore, our measure of each organizational cultural dimension reflects organizational cultural systems built upon employees' perceptions of each cultural value (Kozlowski et al., 2019). Using this firm-year level index, we created the two variables to capture the strength of organizational culture for each of the four dimensions: *Intensity* and *Consistency*. *Intensity* is calculated as the mean of the aforementioned indices across the sample period. *Consistency* is calculated using the coefficient of the variation measure, which is a standardized measure of dispersion and defined as the ratio of the standard deviation to the mean, for those cultural dimensions across the years. We then created a dummy *Strong organizational culture* where both *Intensity* and *Consistency* were above the median values.

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3.5 | Covariates and control variables

The following variables were used as covariate profiles for matching in the panel matching method and as control variables in the fixed effects estimation.

First, to account for differences in the patterns of outflow mobility, we included *direct and indirect outflow concentration scores* by constructing the measures in the same manner as the direct and indirect inflow concentration scores. We also included other variables based on past literature: the *log of the firm's assets*, *leverage*, *book-market ratio*, *capital-sales ratio*, and *EBIT (earnings before interest and taxes) intensity*, in order to account for differences in firm size, proportion of fixed costs, favorable investment opportunity, growth opportunity, and efficiency of a firm's operations, respectively.[9] We also included a dummy variable indicating whether the firm was featured in *Fortune's 100 Best Companies to Work for* in the previous year to capture the firms' reputation in the labor market. The *industry segment Herfindahl index* is also included to take into account the extent of diversification, and the *log number of firms in the primary industry* to account for the competition faced by the focal firm.

We also included other types of employee mobility flow-related variables. First, we included the *total number of employees* in a particular year, *turnover rate*, and *entry rate* to capture the amount of mobility flows. We also included the number of alter firms (i.e., the number of firms that the focal firm hires from) in the focal firm's mobility flow network by including the *outflow and inflow degree centralities*.[10]

4 | RESULTS

Table 1 contains summary statistics and bivariate correlations. Given extreme outliers, we winsorized all variables at the 97.5% level for our main analysis, following the convention in past literature (see Sullivan et al., 2021).

We observed that some of the main variables are highly correlated (e.g., Inflow Centralities and Direct Inflow Concentration Scores). Following previous studies where high multicollinearity among a set of variables was a concern (Galunic et al., 2012; Greve & Seidel, 2015; Hiatt et al., 2009), we used an orthogonalization procedure to partial out common variance among those four variables. In particular, we employed a Gram–Schmidt procedure (Golub & Van Loan, 2013) which generates new orthogonalized measures for those four network variables. We tested for multicollinearity among variables including orthogonalized ones and found that the average variable inflation factor (VIF) is 1.39 with all individual VIF values being below 10, the rule-of-thumb threshold (O'Brien, 2007). Analyses using these

[9]Existing research such as Sorensen and Sorenson (2007) indicates that high-performance firms typically employ a higher proportion of high-performing individuals. Therefore, including these measures allows us to indirectly account for the performance of employees.

[10]In the network literature, status is often assessed using Bonacich's (1987) framework, which conceptualizes status as a function of being connected to highly connected others. In our context, this corresponds to calculating an inflow-based concentration measure, with the coupling coefficient c set at its maximum possible value of 0.99 (Bothner et al., 2010). This approach ensures that a firm's employee-mobility-based status is influenced not only by its direct inflows but also by the structural configuration of inflows within its direct alters' networks, capturing the broader relational dynamics that contribute to its position. In line with this discussion, we tested whether the results are consistent when Bonacich-based status measure is used in place of degree centrality and found that the results remain consistent. These results are available upon request.

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TABLE 1 Summary statistics and correlations.

	Mean	SD	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
[1] Assets (log)	7.149	(1.949)	1.000															
[2] Leverage	0.801	(1.755)	0.218	1.000														
[3] Book-Market R	0.021	(0.060)	−0.237	0.033	1.000													
[4] Capital-Sales R	0.075	(0.164)	0.056	0.025	−0.057	1.000												
[5] EBIT Intensity	0.031	(0.183)	0.393	0.057	−0.021	−0.219	1.000											
[6] Ind Seg H-Index	0.117	(0.196)	0.257	0.076	−0.021	−0.039	0.126	1.000										
[7] Firms Ind (log)	4.113	(1.556)	−0.164	−0.094	−0.054	0.105	−0.269	−0.248	1.000									
[8] Fortune 100	0.012	(0.107)	0.103	−0.002	−0.032	−0.006	0.046	−0.012	0.019	1.000								
[9] Emp (log)	0.936	(1.883)	0.706	0.147	−0.157	−0.142	0.439	0.251	−0.366	0.107	1.000							
[10] Turnover Rate	0.125	(0.061)	−0.280	−0.039	0.049	−0.034	−0.276	−0.095	0.074	−0.030	−0.165	1.000						
[11] Enter Rate	0.163	(0.076)	−0.247	−0.050	−0.008	0.132	−0.140	−0.131	0.128	0.008	−0.189	0.127	1.000					
[12] Out Cent (log)	2.812	(1.160)	0.584	0.109	−0.219	−0.090	0.219	0.087	−0.126	0.149	0.677	0.077	−0.121	1.000				
[13] In Cent (log)	2.883	(1.142)	0.594	0.106	−0.241	−0.049	0.234	0.075	−0.098	0.153	0.654	−0.097	0.072	0.898	1.000			
[14] D Out Concent	0.520	(0.767)	0.507	0.085	−0.151	−0.072	0.175	0.099	−0.107	0.185	0.595	0.038	−0.084	0.836	0.770	1.000		
[15] D In Concent	0.536	(0.748)	0.519	0.078	−0.161	−0.052	0.185	0.088	−0.074	0.209	0.583	−0.070	0.022	0.794	0.834	0.934	1.000	
[16] Ind Out Concent	1.954	(0.983)	0.145	0.050	−0.020	−0.147	0.155	0.002	−0.102	0.031	0.274	0.057	−0.041	0.321	0.269	0.154	0.147	1.000
[17] Ind In Concent	2.025	(0.931)	0.139	0.046	−0.053	−0.123	0.153	0.008	−0.039	0.026	0.230	−0.001	0.053	0.255	0.285	0.122	0.127	0.357

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orthogonalized variables produced consistent results as the ones with the unorthogonalized variables. Therefore, we report the results with unorthogonalized variables for easier interpretation.[11]

4.1 | The effect of top-of-the-funnel position within the employee mobility network

We report our baseline results from the fixed-effects regression followed by a panel matching method which can more effectively address the endogeneity issue.

Fixed-effects regression: Models 1–4 in Table 2 provide the results of the fixed-effects regression on patent intensity.[12] Model 1 includes our main independent variables. In Model 2, we control for the direct and indirect outflow concentration scores and add other control variables in Models 3 and 4. Across all models, we see a negative interaction between the direct and indirect inflow concentration scores. This suggests that a high level of direct inflow concentration in conjunction with a low level of indirect inflow concentration—that is, occupying the tip-of-the-funnel position—leads to a higher level of patent intensity for firms. This supports our H1a. We present our results from Model 4 in Figure 2 (top). Estimation from Model 4 suggests that when direct inflow concentration rises from the 5th percentile to the 95th percentile, accompanied by a shift in indirect inflow concentration from high to low, patent intensity exhibits a substantial increase, moving from the 6th percentile to the 78th percentile.

Models 5–8 in Table 2 provide the results of the fixed-effects regression on TFP with the same model specifications. Our key independent variables are introduced in Model 5. Model 6 incorporates controls for both direct and indirect outflow concentration measures. Models 7 and 8 progressively add additional control variables. Across all models, we see a negative interaction between direct and indirect inflow concentration scores. According to Model 8, when direct inflow concentration rises from the 5th to 95th percentile, accompanied by a shift in indirect inflow concentration from high to low, TFP increases from the 34th to 64th percentile. We plot the interaction effect from Model 8 in Figure 2 (bottom). Firms experience higher productivity if they have a greater direct inflow concentration but a lower indirect inflow concentration; in other words, when they hire from a focused set of firms that themselves hire broadly, supporting our H1b. Overall, we find that the network configuration with directly concentrated and indirectly diversified structure is optimal for firm-level performance in terms of both productivity and innovation, with a notably stronger impact on innovation-related outcomes.[13,14]

[11]Results using orthogonalized variables are available upon request.

[12]Since the periods covered by each data source are varying and there are some missing values within the sample period, we used the extrapolation and interpolation schemes to impute missing data. The results are very similar when we retained only the years for which all variables were available. We also confirmed that our results held when we excluded the sample during the periods with some possible external shock impacts like the 2007–2008 financial crisis or COVID-19 pandemic. These results are available upon request.

[13]The strength of our proposed effect may depend on how long the incoming employees have worked in previous outgoing firms. We tested this possibility by including the average of previous tenure among incoming employees into the models, and found similar patterns of results. Results are available upon request.

[14]We conducted additional analyses using alternative innovation output measures—forward citations (5-year window) and the Consolidating-Destabilizing (CD) Index (Funk & Owen-Smith, 2017)—which showed that the tip-of-the-funnel position correlates positively with both measures. A positive CD Index value indicates more disruptive innovation. Results are available upon request. We thank Russell Funk for sharing his data.

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TABLE 2 Estimating the effect of direct and indirect employee mobility outflow and inflow concentration levels on firm performance using fixed-effects regression models.

	DV: Patent intensity				DV: Productivity (TFP)			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Direct inflow concentration	0.011	0.009	0.025	0.025	0.169	0.221	0.073	0.047
	(.149)	(.198)	(.008)	(.009)	(.000)	(.000)	(.032)	(.106)
Indirect inflow concentration	−0.001	0.000	0.001	0.001	0.007	0.012	0.006	0.001
	(.689)	(.843)	(.592)	(.638)	(.132)	(.020)	(.241)	(.781)
Direct inflow concentration × Indirect inflow concentration	−0.009	−0.010	−0.010	−0.010	−0.039	−0.042	−0.032	−0.029
	(.013)	(.005)	(.002)	(.002)	(.003)	(.002)	(.019)	(.009)
Direct outflow concentration		0.015	0.007	0.010		−0.125	0.001	0.017
		(.000)	(.292)	(.166)		(.000)	(.962)	(.253)
Indirect outflow concentration		0.000	0.000	−0.000		−0.007	−0.003	−0.000
		(.938)	(.973)	(.973)		(.066)	(.468)	(.930)
Number of employees (log)			−0.027	−0.012			0.040	−0.208
			(.000)	(.069)			(.021)	(.000)
Turnover rate			−0.010	−0.033			−1.285	−0.168
			(.867)	(.637)			(.000)	(.045)
Enter rate			−0.111	−0.100			0.263	−0.013
			(.025)	(.035)			(.016)	(.871)
Outflow centrality (log)			0.009	0.011			−0.028	−0.026
			(.058)	(.031)			(.044)	(.006)
Inflow centrality (log)			0.006	0.008			0.044	0.002
			(.305)	(.180)			(.001)	(.861)
Assets (log)				−0.020				0.280
				(.004)				(.000)
Leverage				0.001				−0.001
				(.139)				(.485)
Book-market ratio				−0.015				−0.189
				(.824)				(.247)
Capital-sales ratio				−0.017				−0.018
				(.540)				(.835)
EBIT intensity				−0.024				3.521
				(.574)				(.000)
Industry segment Herfindahl index				−0.011				−0.015
				(.141)				(.575)
Num of firms in primary industry (log)				−0.003				0.024
				(.340)				(.009)

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TABLE 2 (Continued)

	DV: Patent intensity				DV: Productivity (TFP)			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Fortune 100 listed				0.002				−0.016
				(.735)				(.586)
Constant	0.011	0.015	0.009	0.138	−0.346	−0.300	−0.305	−2.251
	(.096)	(.039)	(.648)	(.019)	(.000)	(.000)	(.000)	(.000)
Observations	17,327	17,327	17,327	17,327	23,156	23,156	23,156	23,156

Note: *p*-values are in parentheses. All models include firm- and year-fixed effects. Note that not all firms in our sample have granted patents; hence the number of observations for the patent intensity model (Models 1–4) is smaller compared to the models using TFP (Models 5–8). The sample consists of 1797 firms.

Panel matching method: While our baseline model revealed a positive association between the tip-of-the-funnel position and desirable firm-level outcomes, we also found evidence that certain firm characteristics may enable companies to occupy advantageous network positions. Although we controlled for important firm characteristics in our models based on these findings, unobserved differences might still drive both the network position and firm-level outcomes. Using the panel matching method, we can establish a stronger causal relationship between the network position and firm performance.

The results, presented in Table 3 and Figure A2 of the Appendix, show that low indirect inflow concentration in firms with high direct inflow concentration significantly enhances firm performance, particularly with respect to patent intensity, and shows a marginal improvement in TFP over time. This is consistent with our main finding that the tip-of-the-funnel position is associated with superior firm-level outcomes, especially with innovation-related outcomes. Such an effect is not observed when direct inflow concentration was low—that is, when the focal firm has not used a focused hiring strategy and ended up in a maximally diverse position when the source firms switched to a broad hiring strategy.

These findings affirm the robustness of our baseline results using the fixed-effects model, suggesting that the effects of network position exist even when we isolate the effect driven by exogenous variations. The effects that we capture in this analysis are unlikely to be entirely driven by unobserved firm-specific characteristics or agency of the firm. Instead, they highlight that the structural properties of a firm's advantageous network position, in and of themselves, play a significant role in driving firm performance.

In Figure 3, we present an example of a firm that occupies the tip-of-the-funnel position: Nvidia.[15] In 2016, Nvidia hired primarily from two companies, and its direct inflow concentration score was 1.495, placing it in the top 9.2% of our data. The indirect inflow concentration score was 2.053, placing it in the bottom 51.7%. This low score can be mostly attributed to the diverse hiring source of Cisco and Intel, Nvidia's source firms. Notably, in 2016, Nvidia ranked within the top 22.9% of all firms in terms of patent intensity, and impressively, in the top 2.8%

[15]We restricted our analysis to cases where at least five individuals moved from one company to another, ensuring that the observed mobility patterns reflect meaningful interorganizational flows rather than isolated or incidental movements.

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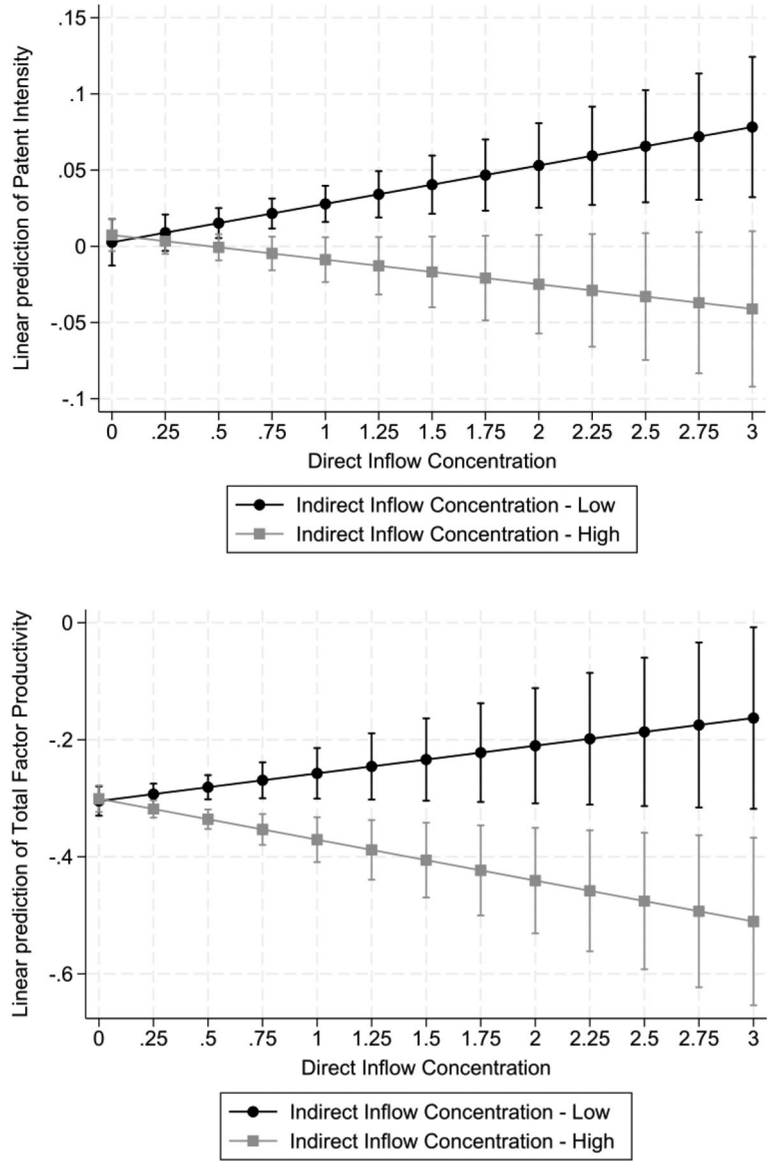


FIGURE 2 Interaction effects of direct and indirect inflow concentration levels on firm-level patent intensity (top) and total factor productivity (bottom).

for TFP. A similar picture emerges when we examine Nvidia's own corporate disclosures. In fiscal year 2016, the company posted a 7% increase in annual revenue—a solid performance that stands out when compared to its key competitors.[16]

[16]Source: https://nvidianews.nvidia.com/news/nvidia-announces-financial-results-for-the-fourth-quarter-and-fiscal-2016?utm_source=chatgpt.com (last accessed on April 1, 2025).

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TABLE 3 Estimated treatment effects of low indirect employee mobility inflow concentration levels on firm performance using matching method for causal inference with time-series cross-sectional data.

		$t+0$	$t+1$	$t+2$	$t+3$	$t+4$
Patent intensity	Overall	0.008	0.013	0.015	0.017	0.013
		(.104)	(.187)	(.247)	(.237)	(.335)
	Direct inflow concentration = low	0.008	0.012	0.013	0.015	0.010
		(.149)	(.269)	(.352)	(.368)	(.516)
	Direct inflow concentration = high	0.009	0.016	0.020	0.026	0.027
		(.009)	(.008)	(.008)	(.004)	(.007)
TFP	Overall	−0.006	−0.022	−0.013	−0.006	−0.004
		(.759)	(.333)	(.616)	(.807)	(.882)
	Direct inflow concentration = low	−0.010	−0.028	−0.021	−0.016	−0.016
		(.667)	(.276)	(.483)	(.577)	(.615)
	Direct inflow concentration = high	0.014	0.013	0.032	0.050	0.062
		(.578)	(.664)	(.329)	(.116)	(.067)

Note: *p*-values are in parentheses. The treatment effect on firms with a high level of direct inflow concentration signifies the effect of occupying the tip-of-the-funnel position.

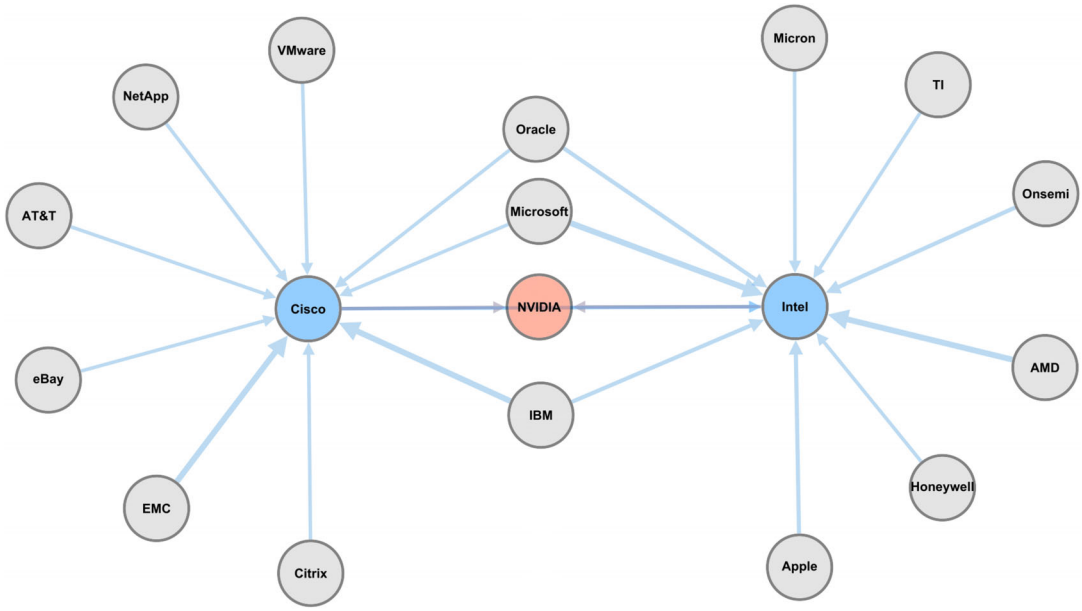


FIGURE 3 Ego-centric employee mobility network of Nvidia for fiscal year 2016.

4.2 | Organizational cultural contingencies of employee mobility network configurations

We next examined how the impacts of the tip-of-the-funnel position may vary depending on organizational culture. Specifically, if the firm has a strong organizational culture, the impact of the tip-of-the-funnel position will be stronger for the performance outcomes of interest.

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In Table 4, we report the results within organizations with a strong culture (i.e., those with high intensity and high consistency). Figure 4 plots the coefficient of the interaction term along with a 95% confidence interval. Note that a negative interaction between direct and indirect inflow concentrations signifies that the tip-of-the-funnel position corresponds to a higher outcome level compared to other positions. As for the patent intensity, we found negative interactions between direct and indirect inflow concentrations when the strength of organizational culture was measured using the following three dimensions: efficiency, diversity, and innovation. As for productivity, we found negative interactions in the collective, efficiency, and diversity dimensions. Results are largely consistent with the idea that alignment between cultural orientation and performance domain amplifies the effect of network position. Organizations with a strong collective and efficiency-based culture achieved higher productivity, while organizations with a strong culture related to diversity and innovation achieved superior innovation outcomes. Interestingly, a strong culture of efficiency also enhanced firms' innovation, while a strong culture of diversity contributed to greater productivity. This suggests that certain cultural dimensions, such as efficiency and diversity, can foster cross-domain complementarities that enhance both productivity and innovation beyond their primary performance domains. In Tables A4 and A5 of the Appendix, we report the results in organizations with a weak culture (i.e., those with low intensity and low consistency). In these models, we do not observe a negative interaction between direct and indirect inflow concentrations across all models.

The set of results provides suggestive evidence that the content of organizational culture as well as its strength are critical for the network positions to function effectively, which supports our prediction in H2a and H2b.

4.3 | Supplementary analysis

Employment duration at the mediating firm[17]: Our paper suggests that hiring at the tip of the funnel allows the focal firm to outsource the integration and coordination of diverse human capital. This mechanism likely requires new hires to have spent sufficient time at the mediating firm. First, regarding knowledge absorption, integration and transfer processes, individuals need time to internalize integrated knowledge. Second, for the coordination and cultural homogenization process, socialization takes time; employees with brief tenures may not have fully assimilated into the organizational culture (Barnard, 1968). Therefore, those with short tenures are unlikely to have fully cycled through these processes and thus may not play a role in transferring human capital to their new employers.

To test this idea, we performed a subsample analysis by re-constructing the mobility network using tenure cutoff points of 6 months, 1 year, and 2 years respectively. Results are reported in Tables A6 and A7 of the Appendix. For patent intensity (Table A6), the tip-of-the-funnel position showed no effect among individuals with tenures shorter than 6 months, 1 year, or 2 years (Models 1–3), but a positive association emerged among those exceeding these thresholds (Models 4–6), consistent with expectations. For productivity (Table A7), no effect appeared for tenures under 6 months (Model 1), and although positive effects were observed for tenures under 1 or 2 years (Models 2 and 3), the coefficients were smaller and less precise than those for longer-tenure samples (Models 5 and 6).

[17]We thank the reviewer team for suggesting this test.

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TABLE 4 Estimating the effect of direct and indirect employee mobility inflow concentration levels on firm performance across organizational cultural levels with a strong culture using fixed-effects regression models.

	DV: Patent intensity				DV: Productivity (TFP)			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Collective	Efficiency	Diversity	Innovation	Collective	Efficiency	Diversity	Innovation
Number of employees (log)	−0.012	−0.023	−0.011	−0.003	−0.262	−0.291	−0.272	−0.289
	(.516)	(.125)	(.479)	(.849)	(.000)	(.000)	(.000)	(.000)
Turnover rate	0.258	0.049	0.294	0.306	0.123	−0.121	−0.255	−0.324
	(.219)	(.861)	(.180)	(.148)	(.625)	(.528)	(.355)	(.109)
Enter rate	−0.037	−0.047	−0.143	−0.089	0.464	0.225	0.140	0.096
	(.450)	(.615)	(.264)	(.447)	(.031)	(.269)	(.563)	(.646)
Outflow centrality (log)	0.021	0.028	0.018	0.030	−0.036	−0.031	−0.018	−0.031
	(.138)	(.103)	(.209)	(.066)	(.232)	(.151)	(.591)	(.204)
Inflow centrality (log)	0.014	0.016	0.028	0.025	−0.033	−0.039	−0.013	−0.004
	(.285)	(.301)	(.140)	(.171)	(.268)	(.101)	(.706)	(.896)
Direct outflow concentration	−0.002	0.009	−0.007	−0.018	0.033	0.053	0.065	0.055
	(.912)	(.573)	(.727)	(.410)	(.285)	(.050)	(.040)	(.039)
Direct inflow concentration	0.013	0.027	0.018	0.018	0.131	0.108	0.083	0.094
	(.519)	(.184)	(.287)	(.317)	(.034)	(.029)	(.112)	(.056)
Indirect outflow concentration	−0.002	−0.004	−0.002	−0.002	−0.003	−0.017	−0.009	−0.004
	(.548)	(.187)	(.691)	(.725)	(.741)	(.047)	(.280)	(.590)
Indirect inflow concentration	−0.011	−0.008	−0.011	−0.009	0.008	0.008	0.001	0.001
	(.033)	(.202)	(.053)	(.112)	(.350)	(.320)	(.912)	(.894)
Direct inflow concentration × Indirect inflow concentration	−0.010	−0.018	−0.016	−0.016	−0.050	−0.042	−0.049	−0.032
	(.172)	(.004)	(.028)	(.039)	(.040)	(.025)	(.029)	(.091)

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TABLE 4 (Continued)

	DV: Patent intensity				DV: Productivity (TFP)			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
	Collective	**Efficiency**	**Diversity**	**Innovation**	**Collective**	**Efficiency**	**Diversity**	**Innovation**
Constant	−0.066	0.048	−0.025	−0.026	−3.015	−2.883	−2.970	−2.735
	(.590)	(.787)	(.849)	(.822)	(.000)	(.000)	(.000)	(.000)
Control variables	Included	Included	Included	Included	Included	Included	Included	Included
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3935	4381	4208	4639	4149	4731	4271	4739

Note: *p*-values are in parentheses. A negative interaction between direct and indirect inflow concentrations signifies that the tip-of-the-funnel position corresponds to a higher outcome level compared to other positions.

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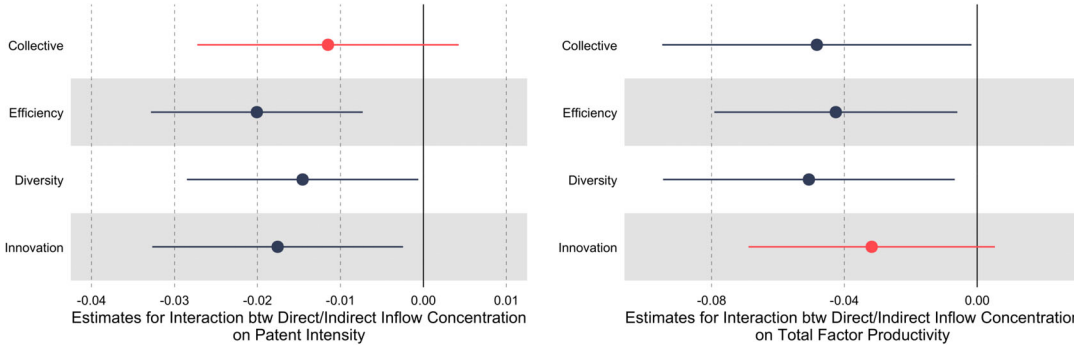


FIGURE 4 Interaction effects of direct and indirect inflow concentration levels on firm-level patent intensity (left) and total factor productivity (right) across four organizational cultural dimensions in organizations with a strong culture. A negative interaction between direct and indirect inflow concentrations signifies that the tip-of-the-funnel position corresponds to a higher outcome level compared to other positions.

Taken together, these results are in line with our conjecture that outsourcing integration and coordination efforts lead to favorable firm outcomes, while also highlighting employment duration as a critical contingency in realizing the benefits of the tip-of-the-funnel position.

5 | DISCUSSION

By integrating insights from the human capital and networks literature, we proposed an advantageous network position that enables hiring organizations to benefit from diverse human capital while externalizing the coordination costs associated with hiring employees of varying backgrounds. We found that such positions allow firms to enjoy higher productivity as well as better innovation outcomes, especially when the firm maintains a strong organizational culture.

5.1 | Contributions

Our study makes important contributions to the extant literature. First, we highlight the significance of considering the composition of the entire incoming workforce, moving beyond the traditional focus on individual hires. Past affiliations have been recognized as valuable information for hiring firms and a means for individuals to signal their abilities and capabilities (Bidwell et al., 2015; Rider & Tan, 2015). Given that individuals accumulate a unique set of experiences from different employers, the human capital endowment of the incoming workforce will vary based on whether it is composed of individuals with a small range of affiliations or those from a variety of affiliations. We discover that there are distinct advantages to hiring from diverse sources, especially when these sources are "filtered" through few organizations. Firms have long externalized training and development through the hiring of experienced workers; we demonstrate that other aspects of human capital management can also be effectively externalized to other firms.

Second, we contribute to the nuanced understanding of firm-specific human capital. Previous research on firm-specific human capital has primarily focused on skills developed within a

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single employer and considered implications of a single move to another employer. We build on previous work that suggested that certain kinds of human capital can potentially cause interference with adaptation in the new organization (Dokko et al., 2009). By recognizing them as a type of firm-specific human capital, we theorize that they are transferred from one firm to another, but not beyond the directly connected alters.

Third, our approach introduces the network perspective to the study of employee mobility, a method that goes beyond the traditional analysis of individual career moves. A detailed map of the mobility network not only reveals the patterns of movement but also highlights the interconnectedness of firms through the flow of human capital. It allows us to see how certain positions within these networks can create an advantage when sourcing talent from other firms. This network-centric view offers an opportunity to investigate how knowledge, skills, and cultural norms are disseminated across firms, enriching our understanding of firms' talent acquisition strategy that could lead to important organizational outcomes.

We also make contributions to the network literature. While sporadic attempts have been made to conceptualize the labor market as a network of connections between firms driven by employee mobility (Sørensen, 1977; Tomaskovic-Devey, 2013; White, 1970), the majority of these efforts have been descriptive or concentrated on the emergent properties of intra-organizational job mobility structures (McDonald & Benton, 2017; Wilcox et al., 2022). As a result, they have often overlooked the important question of how these employee mobility network structures relate to firm performance. To the best of our knowledge, our study represents the first comprehensive examination of employee mobility network properties and their implications for organizational performance across the entire universe of US-listed companies over a recent decade.

Moreover, our measure of organizational culture significantly extends the prevailing conceptualization and measurement strategies of organizational culture in the literature. Whereas many of the previous studies on organizational culture have examined how either specific contents or particular structural characteristics of organizational culture relate to organizational outcomes (Corritore et al., 2020; Harrison & Carroll, 2006), we use a novel approach that simultaneously takes into consideration both contents and structures (Chatman et al., 2014) and incorporates a longitudinal perspective. The structure of organizational culture reveals how core values, beliefs, and norms are distributed and reinforced and are consistently practiced within the organization. Yet without understanding the content of organizational culture, it is difficult to recognize how specifically those cultural values and norms are aligned with organizational goals. We believe that this dual consideration of strength and content allows for a more accurate and holistic analysis of how organizational cultural orientation shapes and is shaped by its employee mobility patterns and how it facilitates goal attainment, meriting further attention.

Our work also builds upon and extends the fragility (equivalent to our measure of concentration) and robustness measure proposed by Bothner et al. (2010). While their approach of full coupling—that is, the comprehensive consideration of network spillovers—captures both first- and higher-order network characteristics simultaneously, it cannot disentangle the distinct contributions of each. This makes it difficult to pinpoint the specific sources and mechanisms underlying an actor's positional fragility. In our work, by distinguishing between first-order measures and those from the higher order, we discover that a high concentration of first-order ties is beneficial, while a low concentration level is preferable for second-order ties.

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5.2 | Limitations and future research

While our study seeks to make meaningful contributions to the literature, our work also has the following limitations. First, our analysis primarily focuses on career moves across public firms. Since we utilize the Herfindahl index as our concentration measure, we expect that the exclusion of moves from private firms, which are typically smaller and presumably less represented in the incoming workforce, should minimally impact our results. Future research could benefit from incorporating data from both the public and private sectors to offer a more comprehensive overview of mobility patterns and their effects on firm performance. Such an approach will also allow for an exploration of workforce diversity in terms of organizational sizes and types.

Second, career moves individuals make result from a complex interplay of matches between organizational and personal choice, market conditions, and organizational strategies, making them inherently non-random. This complexity presents challenges in establishing direct causal links between mobility patterns and firm outcomes. We have sought to address this challenge using a panel matching approach. Nonetheless, the results should be interpreted with caution.

Third, while we assumed that general human capital is largely portable across organizations and firm-specific human capital is not, future research could further examine the contingencies that shape the degree of portability based on the characteristics of the firms that send and receive employees. We also treated the roles of mediating firms as largely homogeneous, assuming that knowledge acquisition and socialization processes unfold similarly across organizations. However, factors such as a firm's organizational culture, strategic orientation, or industry context may differentially influence these processes, thereby affecting both the portability of certain forms of human capital and the extent to which the receiving firm can absorb and leverage that knowledge.

Fourth, while our study suggests that organizations can access diverse skills, experiences, and perspectives by occupying certain network positions, they may also achieve similar diversity by hiring individuals with broad prior experience (e.g., Crossland et al., 2014; Won & Bidwell, 2023). Future research could further explore these alternative pathways to accessing diverse human capital and examine which strategies are most effective under different organizational or environmental conditions.

Moreover, while our focus on the "tip-of-the-funnel" position enables clearer interpretability, we acknowledge that this analytic simplification does not capture the full range of network complexity present in interorganizational mobility structures. Subsequent research could extend our framework by incorporating richer network metrics, such as betweenness centrality, community detection, or core-periphery structure measures, to capture the broader topologies through which firms access and integrate human capital. In this sense, we hope our contribution serves as a conceptual and empirical starting point for more comprehensive investigations into how firms are embedded within and shaped by dynamic labor mobility networks.

5.3 | Practical implications

Our study also offers implications for practitioners. We recommend that firms carefully evaluate the integration costs associated with hiring from a wide array of firms. If feasible, targeting a select group of firms whose employees can contribute diverse knowledge will be beneficial.

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Achieving this requires a deep understanding of the workforce composition as well as the hiring practices of these target firms.

Further, our findings echo and reinforce the conclusions of numerous previous studies regarding the critical importance of a robust company culture. We suggest that the effectiveness of human resource practices, including recruiting as explored in this study, is significantly amplified by the presence of a strong, well-defined culture. Such culture may serve as a foundation that not only attracts talent aligned with the organization's values but also leverages the human capital of new hires toward the organization's success. Hence, we suggest companies invest in cultivating and maintaining a strong culture that resonates with their strategic vision and operational practices.

ACKNOWLEDGMENTS

Both authors contributed equally and are listed in alphabetical order. We are grateful for the insightful comments and suggestions from Peter Bearman, Matthew Bidwell, Matthew Bothner, Russell Funk, Frédéric Godart, Henrich Greve, Jiwook Jung, Minjae Kim, Sun Hyun Park, Andrew Shipilov, Donald Tomaskovic-Devey, participants in the 2024 People and Organizations Conference and ESMT Berlin Brownbag as well as for the valuable guidance provided by Associate Editor Exequiel Hernandez and two anonymous reviewers.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Revelio Labs (https://www.reveliolabs.com/).

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How to cite this article: Han, S. W., & Won, S. (2026). Hiring at the tip of the funnel: Externalizing the work of integrating and coordinating diverse human capital. *Strategic Management Journal*, *47*(7), 1935–1979. https://doi.org/10.1002/smj.70076

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APPENDIX

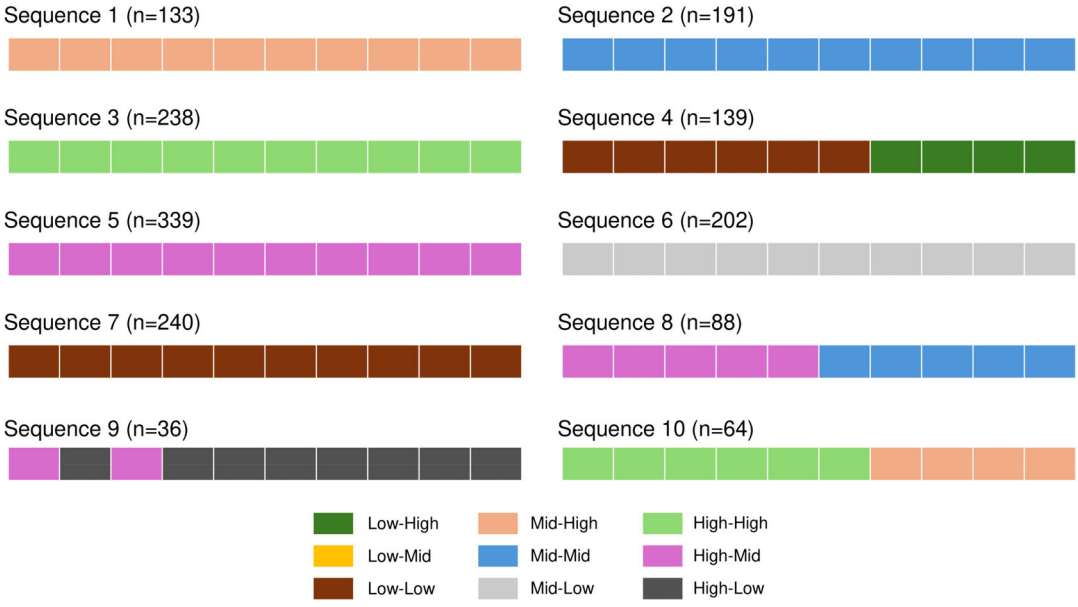


FIGURE A1 Typical sequences of mobility inflow network positions. Sequence analysis treats each firm's annual network configuration as a temporal sequence of categorical states, allowing us to capture typical trajectories. We categorized firms' annual direct inflow concentration into three equal tiers—high, medium, and low—and combined this with their corresponding indirect concentration tiers (e.g., "high-low" indicating high direct and low indirect concentration). Only firms with at least 10 consecutive years of complete data were retained, and we used the most recent 10-year sequence for each firm. We then computed pairwise dissimilarities between firms' sequences using the optimal matching (OM) algorithm, which measures the minimal set of insertions, deletions, and substitutions needed to transform one trajectory into another. Substitution costs were weighted by observed transition frequencies (so that more common transitions were considered less costly), and insertion/deletion costs were fixed at 1. We applied hierarchical clustering (Ward's method) to the resulting dissimilarity matrix, identifying 10 distinct and representative sequence types that capture the dominant pathways of firms' movement across network positions.

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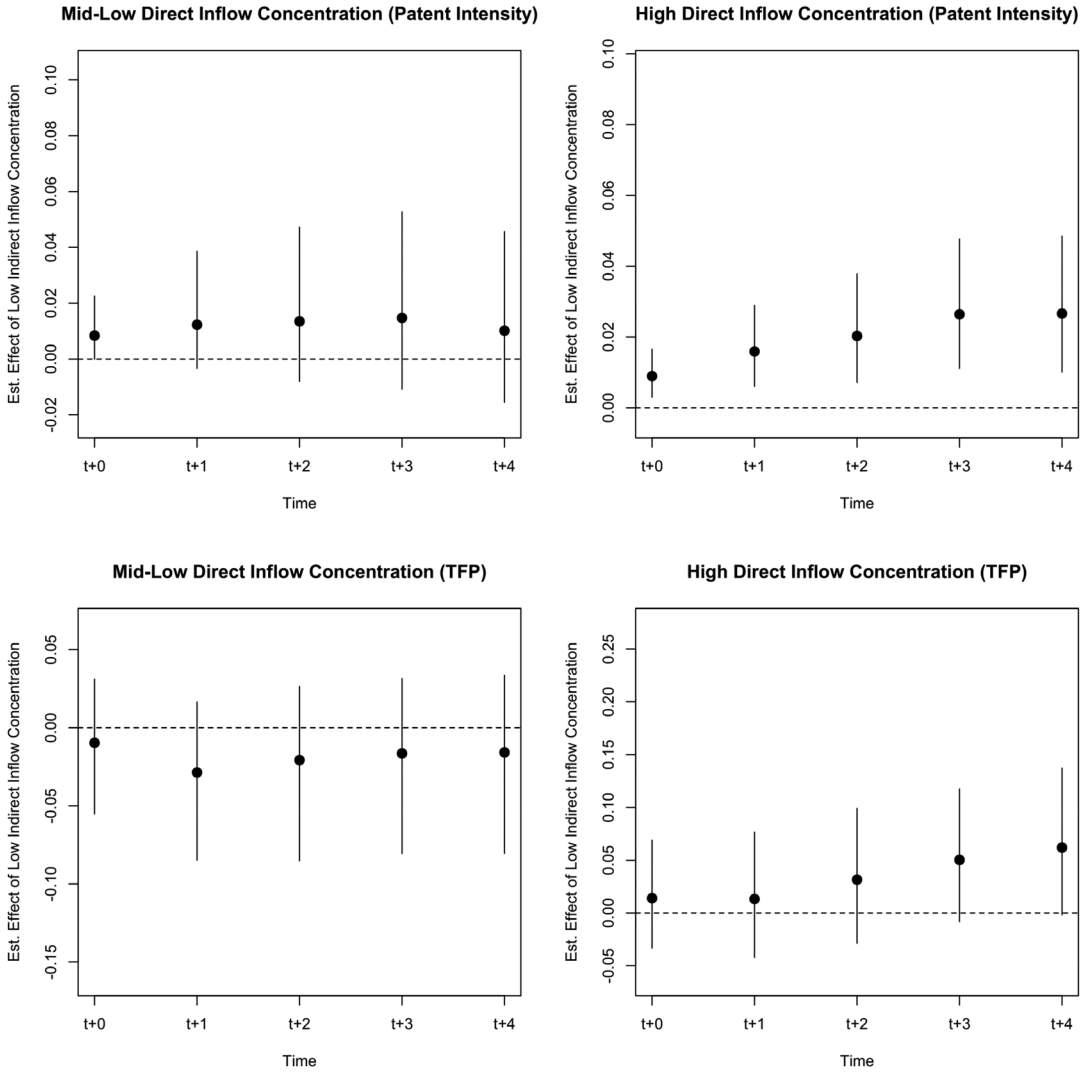


FIGURE A2 Estimated effects of low indirect inflow concentration levels on firm performance using panel matching method. The treatment effect on firms with a high level of direct inflow concentration (the two graphs on the right-hand side) signifies the effect of occupying the tip-of-the-funnel position.

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TABLE A1 Estimating the effect on direct inflow concentration using fixed-effects regression models.

	DV: Direct inflow concentration Model 1
Assets (log)	0.018
	(.091)
Leverage	−0.003
	(.093)
Book-market ratio	0.166
	(.004)
Capital-sales ratio	−0.035
	(.029)
EBIT intensity	0.021
	(.254)
Industry segment Herfindahl index	−0.013
	(.752)
Number of firms in primary industry (log)	0.014
	(.122)
Fortune 100 listed	0.135
	(.009)
Number of employees (log)	0.035
	(.001)
Turnover rate	−0.175
	(.002)
Enter rate	0.318
	(.000)
Outflow centrality (log)	−0.085
	(.000)
Inflow centrality (log)	0.315
	(.000)
Direct outflow concentration	0.416
	(.000)
Indirect outflow concentration	0.001
	(.560)
Indirect inflow concentration	−0.032
	(.000)
Constant	−0.399
	(.000)
Firm fixed-effects	Yes
Year fixed-effects	Yes
Observations	30,919

Note: *p*-values are in parentheses.

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TABLE A2 Multinomial fixed-effects regression results.

	Diverse-diverse	Diverse-concentrated	Concentrated-concentrated
Assets (log)	−1.081	−1.120	−0.297
	(.000)	(.000)	(.087)
Leverage	−0.009	0.010	0.002
	(.845)	(.839)	(.957)
Book-market ratio	3.260	1.993	1.211
	(.062)	(.229)	(.443)
Capital-sales ratio	−0.949	−2.625	0.963
	(.344)	(.075)	(.189)
EBIT intensity	−2.384	−3.000	−0.388
	(.059)	(.024)	(.689)
Industry segment Herfindahl index	−0.213	−0.864	0.248
	(.647)	(.109)	(.462)
Number of firms in primary industry (log)	0.038	−0.117	−0.076
	(.797)	(.386)	(.505)
Fortune 100 listed	−39.544	−13.022	0.134
	(.000)	(.000)	(.661)
Number of employees (log)	0.386	0.391	0.460
	(.136)	(.181)	(.009)
Turnover rate	3.151	3.457	2.101
	(.085)	(.091)	(.145)
Enter rate	−10.309	−8.369	0.014
	(.000)	(.000)	(.990)
Outflow centrality (log)	−0.274	−0.012	0.100
	(.302)	(.971)	(.528)
Inflow centrality (log)	−0.778	−0.749	0.145
	(.000)	(.000)	(.286)
Direct outflow concentration	−1.474	−2.410	−0.628
	(.107)	(.105)	(.005)
Indirect outflow concentration	0.110	0.094	0.049
	(.102)	(.173)	(.409)
Total factor productivity	0.165	0.249	−0.064
	(.437)	(.292)	(.707)
Firm fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes

Note: *p*-values are in parentheses. Baseline category is the Concentrated-Diverse, or the "tip of the funnel" position.

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TABLE A3 List of keywords for semantic dimensions of organizational cultural dimensions.

Dimension	Keywords
Collective	collective, cohesion, cohesive, mutual, shared, communal, normative, unity, harmony, joint
Efficiency	incremental, refine, finetune, improve, hone, refinement, improvement, enhance, optimize, strengthen
Diversity	diversity, variety, various, multiplicity, distinctive, heterogeneous, manifold, diverse, multicultural, distinction
Innovation	innovation, invention, patenting, entrepreneurialism, explore, exploration, creativity, revolutionary, groundbreaking, transform

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TABLE A4 Estimating the effect of direct and indirect employee mobility inflow concentration levels on firm-level patent intensity within organizations with weak culture using fixed-effects regression models.

	Model 1 Collective	Model 2 Efficiency	Model 3 Diversity	Model 4 Innovation
Assets (log)	−0.022	−0.008	−0.008	−0.006
	(.186)	(.252)	(.411)	(.388)
Leverage	−0.000	0.001	0.000	0.000
	(.671)	(.222)	(.796)	(.614)
Book-market ratio	−0.085	−0.076	0.042	−0.067
	(.343)	(.292)	(.672)	(.233)
Capital-sales ratio	−0.124	−0.007	−0.014	−0.003
	(.253)	(.725)	(.523)	(.909)
EBIT intensity	−0.020	−0.020	−0.049	−0.042
	(.558)	(.342)	(.102)	(.019)
Industry segment Herfindahl index	−0.022	−0.013	−0.029	−0.016
	(.089)	(.072)	(.009)	(.038)
Number of firms in primary industry (log)	−0.012	−0.002	−0.010	−0.005
	(.067)	(.701)	(.102)	(.360)
Fortune 100 listed	0.013	0.010	0.004	0.004
	(.554)	(.130)	(.856)	(.812)
Number of employees (log)	−0.008	−0.019	−0.020	−0.018
	(.433)	(.014)	(.036)	(.027)
Turnover rate	−0.015	0.003	−0.002	0.035
	(.806)	(.927)	(.955)	(.273)
Enter rate	0.025	0.017	0.046	0.061
	(.782)	(.746)	(.419)	(.212)
Outflow centrality (log)	−0.011	0.000	0.005	−0.001
	(.136)	(.991)	(.531)	(.772)
Inflow centrality (log)	−0.002	−0.000	0.005	−0.004
	(.870)	(.983)	(.610)	(.636)
Direct outflow concentration	0.016	0.024	0.016	0.016
	(.330)	(.133)	(.343)	(.227)
Direct inflow concentration	−0.014	0.003	0.002	0.005
	(.471)	(.870)	(.912)	(.736)
Indirect outflow concentration	0.002	0.003	0.003	0.003
	(.550)	(.133)	(.351)	(.129)
Indirect inflow concentration	−0.003	−0.001	−0.001	−0.000
	(.346)	(.496)	(.768)	(.955)
Direct outflow concentration × Indirect outflow concentration	0.011	−0.002	0.004	0.001
	(.200)	(.799)	(.625)	(.889)

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TABLE A4 (Continued)

	Model 1 Collective	Model 2 Efficiency	Model 3 Diversity	Model 4 Innovation
Direct inflow concentration × Indirect inflow concentration	0.007	0.001	−0.004	0.000
	(.303)	(.868)	(.600)	(.991)
Constant	0.234	0.067	0.084	0.066
	(.062)	(.144)	(.233)	(.138)
Firm fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Observations	2621	2654	2771	2654

Note: *p*-values are in parentheses. Observation numbers differ in each model since we divided the sample at the median value.

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TABLE A5 Estimating the effect of direct and indirect employee mobility inflow concentration levels on firm-level total factor productivity within organizations with weak culture using fixed-effects regression models.

	Model 1 Collective	Model 2 Efficiency	Model 3 Diversity	Model 4 Innovation
Assets (log)	0.311	0.273	0.249	0.288
	(.000)	(.000)	(.000)	(.000)
Leverage	−0.002	−0.003	−0.003	−0.001
	(.780)	(.742)	(.415)	(.868)
Book-market ratio	−0.073	0.724	0.464	0.845
	(.858)	(.001)	(.011)	(.000)
Capital-sales ratio	0.269	−0.213	−0.165	0.186
	(.121)	(.376)	(.432)	(.316)
EBIT intensity	3.489	3.600	3.505	3.468
	(.000)	(.000)	(.000)	(.000)
Industry segment Herfindahl index	−0.018	0.001	−0.017	−0.044
	(.759)	(.985)	(.720)	(.384)
Number of firms in primary industry (log)	0.026	0.004	0.019	0.049
	(.145)	(.847)	(.094)	(.004)
Fortune 100 listed	0.033	−0.047	0.023	0.029
	(.765)	(.823)	(.786)	(.745)
Number of employees (log)	−0.241	−0.178	−0.168	−0.209
	(.000)	(.000)	(.000)	(.000)
Turnover rate	0.044	−0.136	−0.084	−0.136
	(.788)	(.461)	(.613)	(.390)
Enter rate	−0.035	0.050	0.071	−0.050
	(.815)	(.734)	(.648)	(.707)
Outflow centrality (log)	−0.019	−0.011	−0.002	−0.000
	(.242)	(.600)	(.897)	(.987)
Inflow centrality (log)	−0.006	−0.024	−0.033	−0.002
	(.809)	(.387)	(.161)	(.934)
Direct outflow concentration	0.107	0.009	0.046	0.119
	(.225)	(.902)	(.541)	(.065)
Direct inflow concentration	0.008	0.076	0.066	−0.004
	(.922)	(.433)	(.487)	(.962)
Indirect outflow concentration	0.005	0.007	0.010	0.009
	(.452)	(.280)	(.118)	(.126)
Indirect inflow concentration	−0.002	−0.007	−0.004	0.003
	(.793)	(.418)	(.644)	(.665)
Direct outflow concentration × Indirect outflow concentration	−0.067	−0.045	−0.033	−0.072
	(.053)	(.121)	(.238)	(.012)

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TABLE A5 (Continued)

	Model 1 Collective	Model 2 Efficiency	Model 3 Diversity	Model 4 Innovation
Direct inflow concentration × Indirect inflow concentration	−0.003	−0.026	−0.042	−0.042
	(.923)	(.504)	(.264)	(.267)
Constant	−2.483	−2.191	−2.082	−2.490
	(.000)	(.000)	(.000)	(.000)
Firm fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Observations	3215	3606	3454	3406

Note: *p*-values are in parentheses. Observation numbers differ in each model since we divided the sample at the median value.

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TABLE A6 Estimating the effect of direct and indirect employee mobility outflow and inflow concentration levels on patent intensity using fixed-effects regression models.

	DV: Patent intensity					
	Model 1 (<6 months)	**Model 2 (<1 year)**	**Model 3 (<2 years)**	**Model 4 (>6 months)**	**Model 5 (>1 year)**	**Model 6 (>2 years)**
Assets (log)	−0.008	−0.016	−0.014	−0.018	−0.017	−0.014
	(.043)	(.040)	(.079)	(.009)	(.021)	(.022)
Leverage	−0.000	0.001	0.001	0.001	0.001	0.001
	(.651)	(.121)	(.136)	(.175)	(.232)	(.315)
Book-market ratio	−0.016	−0.065	0.041	0.017	−0.015	0.008
	(.725)	(.284)	(.682)	(.814)	(.784)	(.914)
Capital-sales ratio	−0.010	−0.023	−0.024	−0.021	−0.019	−0.037
	(.190)	(.560)	(.483)	(.479)	(.481)	(.305)
EBIT intensity	−0.048	−0.023	−0.014	−0.009	−0.019	−0.022
	(.002)	(.162)	(.706)	(.840)	(.619)	(.644)
Industry segment Herfindahl index	−0.006	−0.008	−0.011	−0.011	−0.013	−0.011
	(.253)	(.216)	(.136)	(.153)	(.067)	(.093)
Num of firms in primary industry (log)	0.002	0.000	−0.001	−0.002	−0.002	−0.001
	(.417)	(.855)	(.744)	(.411)	(.468)	(.767)
Fortune 100 listed	0.007	0.004	0.001	0.002	0.001	0.003
	(.197)	(.388)	(.853)	(.737)	(.831)	(.539)
Number of employees (log)	−0.008	−0.006	−0.006	−0.011	−0.008	−0.011
	(.002)	(.030)	(.297)	(.086)	(.159)	(.029)
Turnover rate	0.010	−0.060	−0.003	0.005	−0.015	0.043
	(.526)	(.091)	(.963)	(.949)	(.828)	(.560)
Enter rate	−0.020	−0.051	−0.101	−0.095	−0.096	−0.082
	(.135)	(.036)	(.008)	(.049)	(.040)	(.046)
Outflow centrality (log)	−0.002	0.002	0.003	0.009	0.010	0.011
	(.352)	(.377)	(.472)	(.037)	(.058)	(.017)
Inflow centrality (log)	0.005	0.009	0.007	0.007	0.003	0.007
	(.021)	(.005)	(.022)	(.136)	(.463)	(.088)
Direct outflow concentration	0.007	0.012	0.009	0.008	0.007	0.000
	(.002)	(.000)	(.041)	(.245)	(.360)	(.935)
Direct inflow concentration	0.001	0.001	0.002	0.022	0.018	0.012
	(.686)	(.750)	(.687)	(.016)	(.075)	(.046)
Indirect outflow concentration	0.000	0.000	−0.002	−0.000	−0.000	−0.002
	(.370)	(.453)	(.232)	(.928)	(.956)	(.221)
Indirect inflow concentration	0.001	0.000	−0.003	0.000	−0.003	−0.001
	(.013)	(.944)	(.021)	(.990)	(.408)	(.645)
	−0.000	−0.001	0.000	−0.009	−0.007	−0.006

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TABLE A6 (Continued)

	DV: Patent intensity					
	Model 1 (<6 months)	**Model 2 (<1 year)**	**Model 3 (<2 years)**	**Model 4 (>6 months)**	**Model 5 (>1 year)**	**Model 6 (>2 years)**
Direct inflow concentration × Indirect inflow concentration	(.592)	(.498)	(.815)	(.003)	(.041)	(.010)
Constant	0.078	0.128	0.122	0.127	0.135	0.101
	(.008)	(.028)	(.040)	(.026)	(.021)	(.030)
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7414	11,104	14,017	16,953	16,423	15,087

Note: *p*-values are in parentheses. For each model, we performed a subsample analysis by re-constructing the mobility network using tenure cutoff points of 6 months (Models 1 and 4), 1 year (Models 2 and 5), and 2 years (Models 3 and 6), respectively.

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TABLE A7 Estimating the effect of direct and indirect employee mobility outflow and inflow concentration levels on total factor productivity using fixed-effects regression models.

	DV: Productivity (TFP)					
	Model 1 (<6 months)	**Model 2 (<1 year)**	**Model 3 (<2 years)**	**Model 4 (>6 months)**	**Model 5 (>1 year)**	**Model 6 (>2 years)**
Assets (log)	0.293	0.280	0.290	0.283	0.284	0.292
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Leverage	−0.003	−0.003	−0.002	−0.002	−0.001	−0.001
	(.257)	(.140)	(.429)	(.360)	(.553)	(.481)
Book-market ratio	−0.116	−0.110	−0.265	−0.032	0.009	−0.020
	(.738)	(.648)	(.236)	(.776)	(.935)	(.872)
Capital-sales ratio	0.141	0.024	0.023	−0.008	−0.001	−0.029
	(.250)	(.852)	(.794)	(.933)	(.992)	(.771)
EBIT intensity	3.119	3.297	3.444	3.507	3.498	3.511
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Industry segment Herfindahl index	0.010	−0.026	−0.023	−0.016	−0.019	−0.021
	(.791)	(.376)	(.385)	(.542)	(.489)	(.418)
Num of firms in primary industry (log)	0.031	0.020	0.030	0.024	0.022	0.022
	(.006)	(.122)	(.002)	(.008)	(.016)	(.018)
Fortune 100 listed	−0.012	−0.013	−0.013	−0.016	−0.016	−0.016
	(.702)	(.671)	(.677)	(.597)	(.595)	(.588)
Number of employees (log)	−0.235	−0.223	−0.230	−0.211	−0.216	−0.225
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Turnover rate	−0.493	−0.318	−0.274	−0.105	−0.160	−0.195
	(.000)	(.002)	(.002)	(.193)	(.061)	(.024)
Enter rate	−0.030	−0.016	−0.004	0.009	0.008	0.033
	(.798)	(.870)	(.959)	(.912)	(.920)	(.686)
Outflow centrality (log)	0.016	0.004	−0.011	−0.026	−0.027	−0.022
	(.272)	(.762)	(.286)	(.007)	(.007)	(.020)
Inflow centrality (log)	−0.005	−0.019	0.002	−0.009	−0.013	−0.017
	(.758)	(.115)	(.833)	(.386)	(.226)	(.119)
Direct outflow concentration	−0.019	−0.014	0.008	0.011	0.018	0.013
	(.317)	(.463)	(.621)	(.465)	(.223)	(.395)
Direct inflow concentration	0.025	0.070	0.064	0.058	0.062	0.071
	(.334)	(.004)	(.019)	(.059)	(.060)	(.022)
Indirect outflow concentration	−0.002	0.002	0.002	−0.003	−0.002	−0.001
	(.340)	(.449)	(.330)	(.361)	(.492)	(.609)
Indirect inflow concentration	−0.001	0.004	0.002	0.004	0.004	0.003
	(.671)	(.196)	(.506)	(.275)	(.361)	(.442)
	−0.006	−0.018	−0.029	−0.029	−0.029	−0.033

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TABLE A7 (Continued)

	DV: Productivity (TFP)					
	Model 1 (<6 months)	**Model 2 (<1 year)**	**Model 3 (<2 years)**	**Model 4 (>6 months)**	**Model 5 (>1 year)**	**Model 6 (>2 years)**
Direct inflow concentration × Indirect inflow concentration	(.419)	(.021)	(.002)	(.007)	(.008)	(.001)
Constant	−2.362	−2.257	−2.376	−2.260	−2.248	−2.303
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9599	14,919	18,897	22,694	21,973	20,216

Note: *p*-values are in parentheses. For each model, we performed a subsample analysis by re-constructing the mobility network using tenure cutoff points of 6 months (Models 1 and 4), 1 year (Models 2 and 5), and 2 years (Models 3 and 6), respectively.

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