LEARNING BY HIRING: THE EFFECTS OF SCIENTISTS' INBOUND MOBILITY ON RESEARCH PERFORMANCE IN ACADEMIA

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Abstract

This study investigates the effects of scientists' inbound mobility on the research performance of incumbent scientists in an academic setting. The theoretical framework integrates insights from learning theory and social comparison theory to suggest two main mechanisms behind these effects, localized learning and social comparison. The authors propose several hypotheses about the conditions that might intensify or weaken such effects. Specifically, the arrival of new scientific personnel is likely to exert stronger positive effects on the performance of incumbent scientists with shorter (cf. longer) organizational tenure; in addition, academic departments with less diversified expertise and with higher levels of internal collaborations likely reap greater benefits from learning by hiring. The empirical findings, based on a longitudinal analysis of a sample of 94 U.S. academic chemical engineering departments, provide empirical support for these contentions.

The inbound mobility of scientists represents an effective channel for organizations to acquire external knowledge and technologies (Palomeras and Melero 2010; Song et al. 2003; Tzabbar et al. 2013). Knowledge workers in general and scientists in particular accumulate valuable knowledge and expertise at their workplace, so their inter-organizational movement spurs knowledge diffusion and spillovers (Agarwal et al. 2009; Almeida and Kogut 1999; Argote and Ingram 2000; Rosenkopf and Almeida 2003). Two research approaches in prior literature address the potential performance-related benefits of hiring external scientific personnel. One approach explores the direct effect of inbound employee mobility on post-recruitment organizational performance, usually with an emphasis on the human capital implications of external recruiting. Such research has centered predominantly on the tendency of new hires to replicate behaviors that reflect their past experience (e.g., Boeker 1997; Dokko et al. 2009; Groysberg et al. 2008; Rao and Drazin 2002) or draw on the knowledge stock of their former employer (e.g., Almeida et al. 2003; Rosenkopf and Almeida 2003; Singh and Agrawal 2011; Song et al. 2003). These studies reveal that the act of hiring away talent from rivals might not be sufficient for inter-organizational knowledge transfer, because the performance gains due to inbound mobility are contextually specific. For example, attributes of the new joiners and the hiring firm (Almeida et al. 2003; Song et al. 2003) and the degree to which expertise is firm specific (i.e., embedded in relationships with colleagues) (Groysberg and Lee 2009; Groysberg et al. 2008; Huckman and Pisano 2006) are important contingencies that can enhance or offset performance-related benefits from inbound mobility.

Another research approach investigates the indirect effects on performance, that is, how the research performance of incumbent scientists is influenced by the arrival of new scientists. Although this research stream is relatively sparse, some empirical evidence suggests that in certain circumstances, incumbent researchers draw on a new recruit's knowledge and expertise to pursue innovation activities (Lacetera et al. 2004; Singh and Agrawal 2011; Tzabbar 2009). Singh and Agrawal (2011) highlight the role of direct collaborations between new hires and incumbents for post-recruitment knowledge diffusion; Tzabbar (2009) demonstrates empirically that the arrival of new, technologically distant, star scientists can transform the capabilities of incumbents, especially when the local work environment encourages social interactions and knowledge sharing. Such studies underscore the importance of the local context in shaping a firm’s ability to capitalize on a new recruit’s knowledge. Despite increasing evidence that newly hired scientists can generate spillover effects in the hiring organization, little systematic investigation addresses the underlying mechanisms by which these outcomes occur.

To advance such research, we examine the effects of inbound mobility on incumbent scientists’ performance in academia, using insights from social comparison theory (e.g., Festinger 1954; Kilduff 1990; Kruglanski and Mayseless 1990; O’Reilly et al. 1988) to inform learning by hiring theory (e.g., Rosenkopf and Almeida 2003; Song et al. 2003). Specifically, we are interested in the conditions in which inbound mobility leads to performance gains at the department level, beyond those associated with the new hires’ direct contributions to the department’s research output. We view inbound mobility as a social phenomenon and contend that its impact on incumbents’ performance can be explained by the interplay of two mechanisms: localized learning and social comparison. On the one hand, inbound mobility might spur opportunities for learning, social interaction, and knowledge exchange between incoming and existing faculty members through the mechanism of localized learning; on the other hand, it might prompt incumbents to benchmark their attitudes, performance, and behaviors against incoming faculty members through the mechanism of social comparison. Our theoretical model anticipates specific contingencies that can help elucidate when these mechanisms are stronger or more likely to occur. We look at how certain attributes of existing faculty members (e.g., organizational tenure) and features of the hiring department (e.g., research expertise diversity and level of internal collaborations) make incumbents more or less susceptible to peer effects induced by the new hires.

We use the academic department as a unit of analysis. Academic departments are fundamental organizational units in universities; they provide the practices and policies within which the scientific work is conducted (Fox and Mohapatra 2007), and they are relatively autonomous in determining their recruitment policy and the technology for the production of their output (Dundar and Lewis 1995). Therefore, using a department level of analysis (cf. individual level of analysis) allows us to account for potential complementarities between the recruitment policy of the department and other policies, such as those aiming at fostering research specialization and internal collaborations. Academic departments also constitute a local social context, characterized by both spatial and social proximity among faculty members (Aschhoff and Grimpe 2014; Kenney and Goe 2004). This status may induce interdependencies and important externalities among peers (e.g., knowledge spillovers; shared equipment, instrumentation, and facilities; complementary research agendas; internal collaborations) (Carayol and Matt 2004) and activate mechanisms of localized learning and social comparison (Bercovitz and Feldman 2008; Tartari et al. 2014).

We empirically test our theoretical model with a sample of 94 U.S. university departments, specializing in chemical engineering research, for which we analyze their scientist mobility patterns and scientific knowledge production. With this sample, we can track all researcher movements and develop a complete, unbiased picture of mobility. This picture reveals that the arrival of new scientific personnel exerts a stronger positive effect on incumbents' performance if they have a shorter organizational tenure. In addition, departments with more diversified research expertise benefit less from learning by hiring effects. Finally, the positive effects of inbound mobility on incumbents' performance are more intense in departments in which faculty members are more inclined to collaborate internally.

In turn, this study makes both theoretical and empirical contributions to current literature. As a theoretical contribution, our work is novel in its identification of specific contingencies that shape the impact of inbound mobility on the performance of incumbent scientists within the context of academic units. Instead of looking at star scientists and their propensity to generate human capital spillovers (Azoulay et al. 2010; Kehoe and Tzabbar 2015; Lacetera et al. 2004; Oettl 2012; Zucker et al. 2002), we shift the focus to interaction effects and explore when incumbent researchers are more or less susceptible to influences induced by incoming (but not necessarily star) scientists. Overall, our study advances literature on learning by hiring (e.g., Almeida et al. 2003; Rosenkopf and Almeida 2003; Song et al. 2003; Tzabbar 2009) by investigating novel challenges that research-intensive organizations face in capitalizing on the knowledge and expertise of their new recruits. Simultaneously, we add to the scholarly body of work on the role that the localized social environment plays for modeling individual actions and behaviors in academia (e.g., Bercovitz and Feldman 2008; Tartari et al. 2014), by linking it to the phenomenon of inbound scientists' mobility.

Finally, we contribute empirically to literature on the mobility of R&D personnel. Empirical research in this area is limited, mainly by the methodological obstacles associated with tracking all individual scientists' movements, regardless of their patenting and publishing activity. Most prior empirical research has used inventors' patent trajectories and patent citation data to infer individual movements and link them to inter-firm knowledge flows. Such studies valuably demonstrate the role of human mobility as a conduit for knowledge diffusion and highlight important contingencies that can facilitate or hinder this process (Almeida et al. 2003; Rosenkopf and Almeida 2003; Song et al. 2003). Yet most investigations of the mobility of scientists and engineers can identify mobility only if the researcher has patented an invention both before and after changing employers. (They identify a change of employer when two consecutive patent applications by the same inventor are assigned to different assignees.) This approach introduces a potential selection bias that could minimize the costs of mobility or generate false positives (e.g., Ge et al. 2014). In contrast, we use a new, unique data set in which we can track all entries and exits at the academic department level, eliminating this potential bias. Thus we add to empirical literature on individual mobility in other industries (Dokko and Rosenkopf 2010; Groysberg et al. 2008; Huckman and Pisano 2006; Rao and Drazin 2002; Somaya et al. 2008) and at the executive level (Boeker 1997), which tracks mobility using methods specific to distinct study contexts.

THEORY AND HYPOTHESES

Effects of inbound mobility on incumbents' research performance

An organization's research competences reside mainly in the knowledge and skills of its research scientists (Deeds et al. 2000), so the scientific expertise of research-driven organizations likely changes significantly with scientists' recruitment and turnover (Subramaniam and Youndt 2005). Zucker and Darby (1997), for example, illustrate how a large pharmaceutical firm transformed its technological identity primarily by hiring many new scientists with biotechnology backgrounds. Because significant tacit knowledge is embedded in scientists and engineers (Almeida and Kogut 1999; Argote and Ingram 2000), hiring personnel away from other employers is particularly worthwhile if firms want to acquire externally developed expertise (Rosenkopf and Almeida 2003; Song et al. 2003).

The impacts of such inbound mobility on the research performance of a research-driven organization can be direct and indirect. Because incoming scientists embody knowledge and competences that they bring with them when they move, newly hired personnel can participate directly in the knowledge-building processes at the hiring firm and generate direct research outputs. For example, new recruits in academia publish articles with their new affiliation. Accordingly, organizations often enjoy an immediate boost in their performance through external recruiting (Dokko et al. 2009; Rao and Drazin 2002; Rynes et al. 1997). Moreover, recruiting top performers can exert indirect effects on the performance of other scientists in the organization, such as by transforming incumbents' capabilities (Tzabbar 2009) or substantially increasing their productivity (Lacetera et al. 2004). This indirect channel has attracted less attention, but research-driven organizations that want to initiate a change by hiring new scientific personnel need to understand how their incumbent researchers respond to the presence of new, productive colleagues.

In this indirect channel, we view inbound mobility as a social phenomenon that likely shapes the local social dynamics in the hiring organization and affects the research performance of incumbent scientists. When the social context at the workplace is characterized by spatial and social proximity, it likely activates two main social mechanisms: the mechanism of localized learning, through facilitating social interactions and knowledge transfer among local peers (Bercovitz and Feldman 2008), and the mechanism of social comparison, through highlighting the role that peers or relevant others play in modeling individual actions and behaviors (Felps et al. 2009; Tartari et al. 2014). Our central theoretical claim is that inbound mobility likely intervenes in the local social dynamics at the hiring organization, and in certain circumstances, the effects of these two mechanisms are intensified or weakened. To study these effects, we integrate research on learning by hiring and insights from social comparison theory.

On the one hand, the incorporation of new scientists might be beneficial for incumbent scientists' performance, as it likely spurs learning by hiring. For example, Song et al. (2003), Tzabbar (2009), and Zucker and Darby (1997) suggest that hiring away technologically distant scientists is a particularly useful way for firms to learn about external technologies. Some characteristics of the hiring firm, such as size and path dependency, are documented as likely boundary conditions on learning by hiring (Almeida et al. 2003; Song et al. 2003). In addition, the portability of individual performance across organizations depends on the specificity of the new recruits' knowledge (Groysberg and Lee 2009; Groysberg et al. 2008; Huckman and Pisano 2006) and the local social context in the hiring organization (Sigh and Agrawal 2011; Tzabbar 2009). Research underscores that learning concrete analytical skills or procedures often entails frequent interactions with peers (Hasan and Bagde 2013). Tzabbar (2009), for example, examines how the use of a new recruit's prior knowledge by others in the destination firm depends on the existence of firm structures that encourage social interactions and knowledge sharing among peers. Singh and Agrawal (2011) similarly highlight the importance of direct collaborations among researchers for knowledge transmission; among incumbent employees, those who directly collaborate with their new peers reap more benefits from learning by hiring.

On the other hand, the arrival of new, productive scientists might induce peer effects on the performance of research scientists who are already employed by the organization through the mechanism of social comparison. According to social comparison theory, humans tend to evaluate their abilities, opinions, and performance by comparing themselves with others whom they perceive as being similar (Festinger 1954; Kilduff 1990; Kruglanski and Mayseless 1990) or slightly better (O'Reilly et al. 1988) on some set of attributes. Consistent with this logic, co-located work peers are often a target of social comparison (Felps et al. 2009; Tartari et al. 2014). Therefore, through a social comparison theory lens, inbound mobility might invoke social comparison processes among incumbent scientists, motivate them to exert more effort, and improve performance.

We study these effects in the context of academia; we believe academic departments are an excellent setting, in which the mechanisms of localized learning and social comparison are extremely relevant and thus likely to be captured empirically. Academic departments are important organizational subunits with some autonomy (Dundar and Lewis 1995); they provide a local social environment, characterized by both spatial and social proximity (Aschhoff and Grimpe 2014; Kenney and Goe 2004), which often stimulates proactive behavior among department faculty members (Tartari et al. 2014). Whereas face-to-face social interactions among academic department colleagues facilitate localized learning, the tendency of academics to benchmark themselves against department peers of similar rank (e.g., on issues related to salary, promotion and tenure decisions, department and school rankings) encourages such social comparison.

We investigate specific contingencies that likely make incumbents more susceptible to peer effects induced by the new hires. Organizational tenure is one such potential moderator; it is not only one of the job-related demographic attributes that employees often consider when making social comparisons at work (Pelled et al. 1999), but also it affects opportunities for social interactions and knowledge sharing among peers (Ancona and Caldwell 1992; Zenger and Lawrence 1989). Certain features of the hiring department also might intensify or weaken the prevalent tendency of humans to choose similar others when engaging in social interactions (e.g., Kleinbaum et al. 2013) and social comparisons (e.g., Felps et al. 2009). We suggest two such contingent factors are the diversity of a department's research expertise and the department's internal collaborative environment.

Moderating role of incumbents' organizational tenure

Organizational tenure—that is, how long the faculty members have been employed by the focal department—is a central factor to consider when explaining the response of incumbent scientists to the arrival of new colleagues. Specifically, we predict that the social mechanisms of localized learning and social comparison, induced by inbound mobility, are most likely to occur for incumbents with shorter (cf. longer) organizational tenure.

When academics have worked for the focal department for a relatively short time, it is plausible that the resultant social context will make them more likely to be receptive to external information, knowledge, and ideas sourced by the new arrivals, such that they benefit more from learning by hiring. Given that incumbents with shorter (cf. longer) organizational tenure are relatively new to the department, they should be less likely to have developed routines that are socially embedded in the organization (McFadyen and Cannella 2004; Paruchuri et al. 2006). In turn, they should be more open to external influences, willing to engage in informal talks with the new recruits, and reliant on the expertise of their new colleagues as sources of information and feedback. Moreover, the chances that incumbents with shorter (cf. longer) organizational tenure engage in social interactions with new entrants are higher, due to their relative tenure homogeneity (Ancona and Caldwell 1992; O'Reilly et al. 1989; Zenger and Lawrence 1989). Research suggests that employees who share similar organizational tenures communicate, socially interact, and share knowledge and expertise with one another more frequently (Ancona and Caldwell 1992; Zenger and Lawrence 1989). We expect frequent interactions with colleagues and exchanges of helpful comments, encouragement, criticism, and advice to spur knowledge spillovers and localized learning (Azoulay et al. 2010; Bercovitz and Feldman 2008; Oettl 2012; Perretti and Negro 2006; Tzabbar 2009) and thereby boost research performance.

In addition, the mechanism of social comparison, induced by inbound mobility, likely comes to the fore for incumbents with shorter (cf. longer) organizational tenure. We expect short-tenured incumbents to be more inclined to view their newly hired colleagues as yardsticks against which to evaluate their own career progress, so they exert more effort to enhance performance. As noted by Pelled, Eisenhardt, and Xin (1999), organizational tenure is one of the job-related demographic attributes tied to career management that employees consider when making social comparisons at work. People tend to use similar rather than dissimilar others as a desirable standard for comparison (Festinger 1954; Kruglanski and Mayseless 1990). In academia, fellow academics of similar rank that have entered the department at a similar time tend to benchmark themselves with one another (Bercovitz and Feldman 2008); this tendency is even stronger for junior faculty members as they prepare for tenure and promotion and compete for a limited number of senior positions in the department (Tartari et al. 2014). Furthermore, in a context of uncertainty, academics are susceptible to comparing themselves with relative others and engaging in vicarious learning by observing and emulating the behavior of their peers (Aschhoff and Grimpe 2014; Bercovitz and Feldman 2008; Wood and Bandura 1989). For example, research highlights the tendency of university professors to use their departmental peers as a reference point and imprint peers' behaviors when they embrace new initiatives, such as the transition to academic entrepreneurship (Stuart and Ding 2006), participation in technology transfers (Bercovitz and Feldman 2008), and involvement with industry (Aschhoff and Grimpe 2014; Tartari et al. 2014). We contend that incumbents with shorter (cf. longer) organizational tenures are less likely to have achieved professional security; in the face of uncertainty, they are more likely to engage in social comparison with the new hires, exert more effort, and enhance their performance. Taken together, these lines of arguments, emphasizing the mechanisms of localized learning and social comparison, provide consistent insights and suggest the following hypothesis:

Hypothesis 1: Inbound mobility has a more positive effect on the performance of incumbent scientists with shorter (cf. longer) organizational tenure.

Moderating role of a department's research expertise diversity

A growing body of research examines the relationship between the technological diversity (breath or scope) of an organization's knowledge base and its innovation performance (e.g., Miller 2006; Nesta and Saviotti 2005), but our focus is not on the direct effect but rather on how this feature of the hiring department interacts with inbound mobility to affect incumbents' research performance. We contend that when academic departments pursue research endeavors in diverse knowledge domains, the susceptibility of incumbent scientists to peer effects induced by the new hires is likely to be lower, at least at the margin, for several reasons.

Consider first the mechanism of localized learning. Departments with less diverse research expertise face greater chances of intersections, similarities, and overlaps in terms of knowledge, research interests, and backgrounds among faculty members; these chances in turn may enhance the frequency of social interactions and communications among work peers (Kleinbaum et al. 2013; Zenger and Lawrence 1989) and spur knowledge flows and learning opportunities. Haeussler (2011), for example, argues that academics are more likely to exchange information with others if they share similar values, beliefs, and professional identities. Similarly, Reagans (2011) underscores the importance of social similarity and propinquity in facilitating social interaction and generating strong interpersonal ties among work peers. Academics who share similar research expertise often sort themselves into similar situations (Kleinbaum et al. 2013). For example, scientists working on a specific field usually attend the same conferences and workshops, read more of one another's research, and receive training that features similar values, methodologies, and scientific approaches. Despite efforts to integrate different knowledge areas and the benefits that cross-pollination might bring (Lavie and Drori 2012; Miller et al. 2007), a more diversified department, in terms of areas of research, instead will tend to display clusters of localized knowledge. Other things being equal, knowledge will not circulate as fast as it does in a more homogenous department. That is, in a more diversified department, the learning and spillover effects generated by inbound mobility are more likely to remain localized and affect only some of the faculty members, whereas in a more homogenous department, knowledge flows more smoothly, and the benefits will be more widespread.

Social comparison processes likely play a more prominent role in less diversified departments in terms of areas of research expertise; we contend that such departments tend to exhibit higher levels of perceived department homogeneity. When incumbent scientists' expertise spans a relatively narrow range of research areas, the self–other similarity and the interdependencies among department faculty members are likely emphasized; therefore, the social comparison processes are of high relevance, and benchmarking against the attitude, abilities, behavior, and performance of others is more likely to occur

(Molleman et al. 2007; Stapel and Marx 2007). Research suggests that people tend to choose career referents with similar shared attributes, like age or professional experience, that might relate to performance (Gibson and Lawrence 2010). Moreover, sharing a distinctive attribute with colleagues, such as common research expertise or joint group membership, may signal unique similarity and create a sense of closeness and personal bonds that prompt assimilative (rather than contrasting) self-evaluations through social comparisons (Brewer and Weber 1994; Stapel and Marx 2007). In more diversified departments, these social comparison processes not only may be weaker but also should tend to cluster around single research areas. The arrival of new scientists then triggers effort and improves performance only for a subset of the faculty of the receiving department. These effects should be more widespread in less diversified departments, in terms of their areas of research expertise.

Hypothesis 2: The positive effect of recruiting high-quality scientists on the performance of incumbent scientists is weaker for departments with more diversified research expertise.

Moderating role of internal collaborative environment

If scientists' inbound mobility boosts incumbent scientists' performance through the social mechanisms of localized learning and social comparison, we expect that these positive effects will be stronger or more likely in academic departments in which faculty members are more inclined to collaborate internally with their colleagues.

One explanation emphasizes the crucial role of the internal collaborative environment for enhancing inter-organizational knowledge flows. Knowledge sourced through scientists' recruitment diffuses very narrowly in destination firms (Singh and Agrawal 2011), such that the simple act of hiring might not be sufficient for knowledge transfers to take place (Almeida et al. 2003; Song et al. 2003). Appropriate internal structures that facilitate knowledge sharing and social interactions among employees are needed to trigger the mechanism of learning by hiring (Tzabbar 2009). An internal collaborative environment enhances connectivity among departmental colleagues and sets the stage for knowledge exchanges and combinations (Nahapiet and Ghoshal 1998). Joint work on collaborative research projects also fosters repeated social interactions, increased mutual trust and cooperation, and reciprocity among collaborators, prompting fast and more efficient communications through frequent exchanges of tacit knowledge and expertise (Bouty 2000; Lavie and Drori 2012; McFadyen and Cannella 2004; Zucker et al. 2002). The resulting increase in shared understanding and integration of knowledge sourced from newly hired scientists (Tzabbar 2009) then creates opportunities for knowledge brokerage (Hargadon and Sutton 1997), cross-fertilization of ideas (Lavie and Drori 2012), experimentation with innovative projects (Miller et al. 2007; Rosenkopf and Nerkar 2001), and novel knowledge combinations (Ahuja and Lampert 2001; Fleming 2001; Galunic and Rodan 1998). We expect academic departments, in which faculty members tend to collaborate internally, to assimilate and capitalize better on new recruits' knowledge and benefit more from learning by hiring.

Another possible explanation is based on the idea that inter-organizational ties and internal social capital underlie social comparison processes that incentivize co-workers to perform in line with or better that their peers (Maurer et al. 2011). When jobs involve social interaction among peers, social comparisons at work are almost inevitable (Buunk et al. 2005). Thus, whether the work context is cooperative versus competitive is a crucial determinant of the direction of the social comparison effects (Festinger 1954; Stapel and Koomen 2005). Internal cooperation among department faculty members entails joint participation in research endeavors and high levels of mutual trust. Moreover, joint work on research projects involves interdependencies among departmental colleagues, such as pooling scientific expertise and resources (Katz and Martin 1997; Lavie and Drori 2012) or exploiting complementarities among researchers in terms of their research agendas, common instrumentation, and facilities (Carayol and Matt 2004). Such interdependencies urge social comparison among peers and adjustments of individual efforts (Molleman et al. 2007). In cooperative environments, individuals tend to align their self-views with their collaborative partners and emphasize self–other similarities (cf. differences) (Stapel and Koomen 2005). Therefore, internal cooperation likely inspires positive feelings among department colleagues and admiration for others' performance (Smith 2000), which then triggers individual motivation to work hard and improve performance (Molleman et al. 2007). In these circumstances, the response of incumbent scientists to inbound mobility is more likely to entail increased scientific effort and improved research performance. These arguments give rise to the following hypothesis:

Hypothesis 3: The positive effect of inbound mobility on the performance of incumbent scientists is stronger for departments in which faculty members are more inclined to collaborate internally.

METHODS

Research setting

To analyze the effects of scientists' inbound mobility on incumbents' performance empirically, we focus on an academic research sector in the field of chemical engineering in the United States. Chemical engineering is the science of creating economical new chemical processes (Arora and Gambardella 1998); chemical engineers engage in the synthesis, design, testing, scale-up, operation, control, and optimization of processes that change the physical state or chemical composition of materials (CPSMA and DEPS 1988). Chemical engineering departments provide the unit of analysis for this study. Academic departments are fundamental organizational units in colleges and universities; are relatively autonomous in hiring and promoting faculty, determining academic degree standards, and making curriculum decisions (Dundar and Lewis 1995); and generally are evaluated by both their own universities and external agencies (e.g., for accreditation, rankings). We chose this specific research setting on the basis of several considerations.

First, university chemical engineering departments are research-driven organizations; they operate in a research-intensive environment, at the forefront of creating and disseminating scientific knowledge. The process of discovering and exploiting breakthroughs relies heavily on sustained investments, so schools spend heavily on chemical engineering R&D (e.g., in 2003, Massachusetts Institute of Technology spent $17.3 million, North Carolina State University spent $16.8 million, and Pennsylvania State University invested $15.1 million; *Chemical & Engineering News* 2005). Advanced instrumentation, facilities, and supportive mechanisms also are necessary to conduct state-of-the-art research. Depending on the complexity of the research, the required equipment ranges from small, laboratory bench–scale setups and machines that serve a single investigator to synchrotron sources, nuclear reactors, superconducting magnets, sophisticated surgical facilities, and supercomputers employed by vast user communities and research groups (BCST and DELS 2007). Academic researchers might exhibit a certain degree of autonomy in setting up their schedule and choosing their research focus, but equipping their research labs sufficiently is critical to their ability to perform research (*Chemical & Engineering News,* 2000). Thus, academic research in chemical engineering, unlike research in the humanities or social sciences, requires substantial investments to obtain appropriate equipment and facilities.

Second, these departments constitute a local social context that features spatial and social proximity among faculty members (Aschhoff and Grimpe 2014; Kenney and Goe 2004). This context induces interdependencies and important externalities among department colleagues, including critical knowledge spillovers; shared equipment, instrumentation, and facilities; complementarities across different research agendas; and internal collaborations (Carayol and Matt 2004). Collaboration among researchers thus is the norm rather than an exception, as exemplified by the large number of coauthors typically listed on publications. According to the Science Citation Index Expanded, more than 70% of the articles published between 2005 and 2010 in *AIChE Journal* (a broad-based journal of the American Institute of Chemical Engineers) included at least three investigators as co-authors. Joint research between chemical engineering and other university departments also is widespread, because many chemical engineering departments trace their origins to other departments, such as chemistry or mechanical, petroleum, ceramics, mining, sugar, or paper engineering (Rosenberg 1998).

Third, chemical engineering is a rapidly evolving and expanding field, in which the incorporation of new faculty has become increasingly relevant for shaping knowledge bases. For example, the chemical engineering department at Tufts University extended its reach into biological areas by hiring new faculty with specializations in biotechnology, biological transport phenomena, and systems biology (*Chemical & Engineering News* 2001). Many chemical engineering departments even have changed their names (e.g., chemical and environmental engineering, chemical and biochemical engineering, chemical and petroleum engineering), to reflect their broadened focus. Faculty mobility thus is a relevant phenomenon; according to recent findings, the median tenure for U.S. chemical engineering faculty is 11.64 years for men and 9.78 years for women (Kaminski and Geisler 2012).

Fourth, this context offers us a unique opportunity to collect data about all department faculty members over several years and identify precisely both newly hired personnel and incumbents, independent of their publication or patent record. Thus we can conduct a more fine-grained analysis of how incumbents' behaviors might represent responses to inbound mobility and avoid the potential biases that affect previous work (Ge et al. 2014).

Data and sample

To construct the sample, we used the population of 156 chemical engineering departments at universities in the United States, listed in the Chemical Engineering Faculty Directory (we used several editions). This reference book contains contact information for faculty members as well as numbers of degrees granted by each department; we used yearly volumes of this directory. To build the database, we also gathered information from additional sources. Specifically, we used SciVerse Scopus to collect bibliographic information (including citations) about every paper published in indexed journals by each university department in our sample. Data on the publication records of each new hire also came from SciVerse Scopus. We drew on Journal Citation Report–Science Edition for 2000 to identify the impact factor of the journals in which articles had been published. To account for areas of research expertise, we collected data from Thomson Scientific's Science Citation Index Expanded, indicating the subject categories in which each department published. Finally, we matched our sample with data on university R&D expenditures in the subfield of chemical engineering from the Survey of Research and Development Expenditures at Universities and Colleges, provided by the National Science Foundation.

We used the academic department as a unit of analysis (only one chemical engineering department functioned in each university in our study). For each department, we tracked all full-time, tenure-track faculty members (including full professors, associate professors, and assistant professors) annually. We then created a data file, with entry and exit histories for each faculty member. An entry was registered when each professor appeared for the first time on the department faculty list; an exit was recorded when the professor no longer appeared on the list of department faculty. Our final sample is represented by 94 academic departments for which we analyze scientists' mobility patterns over the period 1996–2004.

Measures

Dependent variable. The dependent variable is incumbents' research performance; we are interested in variations in a department's research output in response to inbound mobility, after excluding the direct contributions of the new hires. New recruits get incorporated into each department over a moving window of two years; that is, new recruits are those faculty members that joined the department in years t and t – 1. Incumbents are those faculty members that joined the department prior to t – 1. To construct this variable, we included publications by incumbent scientists only (excluding joint publications between new hires and incumbents). To operationalize incumbents' research performance, we used the number of publications weighted by respective citations. This citation-weighted measure of the total number of publications has been used widely in prior literature to measure the quality and scientific significance of published research (Adams and Clemmons 2011; Cole and Cole 1971; Oettl 2012). Similarly, innovation studies rely on the number of forward citations to gauge the scientific value of patents (e.g., Hall et al. 2001). Consistent with prior work (Adams and Clemmons 2011), we used a five-year window to count citations, which helps eliminate the bias incurred because earlier publications are prone to receive more citations. However, citations to published work exhibit highly skewed distributions, and it is difficult to predict ex ante whether a particular article will be highly cited (Baum 2011). In addition, this measure blends the quantity and quality of publications. To enhance confidence in our findings, we built a second indicator of research performance, based on journals' impact factors, and used it to check the robustness of the results. We proxy incumbents' research performance with the number of publications in science- or engineering-oriented journals with impact factors of 3 or higher (according to Journal Citation Report–Science Edition 2000). Only 15% of journals in our sample surpassed this threshold. This alternative measure assumes a positive correlation between the impact factor of a journal and its quality. In addition, high-impact journals exert greater impacts on the scientific community (McFadyen and Cannella 2004).

According to our theoretical model, the effect of scientific recruitment on production patterns of incumbents should be contingent on their organizational tenure. Therefore, we classified faculty members that joined the department in years t – 2, t – 3, t – 4, and t – 5 as incumbents with shorter organizational tenures; those who arrived in year t – 6 or earlier are incumbents with longer organizational tenures. We recalculated the two measures of incumbents' research performance for each subset of incumbents.

In addition, we calculated the dependent variable (for all incumbents and for each subset) for each year from 1998 to 2006. We used a two-year lag for the dependent variable, after measuring our independent and control variables for each year during the period 1996–2004. This time gap was reasonable for our setting, because publication delays in science tend to be relatively short (Luwel and Moed 1998). The time lag helped mitigate the potential for reverse causality concerns.

Independent variables. The main independent variable is inbound mobility, measured as the sum (for all new hires) of the average impact factor of the journals in which new hires have published within five years prior to joining the focal department. (New hires are the faculty members that joined the department in years t and t – 1). That is,

$$\text{Inbound mobility} = \sum_j \sum_i \frac{IF_{ij}}{N_j},$$

where IF_{ij} is the impact factor of the journal where paper i was published by researcher j, and N_j is the total number of papers published by researcher j within five years prior to the hiring event. Using a five-year window helps attenuate annual fluctuations and better reflects scientists' propensity to publish in high-impact journals prior to hiring. The measure varies with both the average research quality of new hires and their number.

Moderator variables. To measure a department's research expertise diversity, we used 1 minus the Herfindahl index, a standard approach that gives a sense of how focused or diversified the focal department is (e.g., Garcia-Vega 2006). We constructed this variable using the classification of each publication in subject categories, provided by Science Citation Index Expanded:

$$\text{Research expertise diversity} = 1 - \sum_k \left(\frac{N_{sk}}{N_s}\right)^2,$$

where N_{sk} is the number of publications by department s in subject category k over a five-year window (years t to t – 4), and N_s denotes the sum of all papers published by the department in all subject categories for the same period. The measure yields values between 0 and 1, such that larger values correspond to greater diversity.

With our internal collaborative environment variable, we seek to gauge the ties among department members that facilitate internal knowledge flows. We adopted the following measure from prior research (e.g., Hansen et al. 2005):

Internal collaborative environment = Number of unique ties among department members/Total possible number of internal pairwise ties.

To construct this measure, we matched the names of the department faculty with the authors of papers that listed the focal department as their affiliation, and then identified all papers coauthored by at least two department faculty members over a five-year window. A unique tie emerges if two department members have co-authored at least one paper during the time window; the total possible number of such ties is $n \times (n - 1)/2$, where n is the number of professors in the department.

Control variables. We operationalized size as the number of incumbent faculty members each year. Prior work indicates an effect of academic department size on research performance (Hagstrom 1971; Kyvik 1995), so it is appropriate to control for this variable. For exits, we measured the number of scientists leaving the department over a moving window of two years. A significant portion of knowledge is embedded in individual members, and personnel moves may result in knowledge transfers (Argote and Ingram 2000), so we accounted for the potential loss of expertise due to researchers' departures. With R&D intensity, we captured the ratio between total R&D expenditures in the subfield of chemical engineering for each university (millions of U.S. dollars) and the number of faculty members in the focal department. With this variable, we controlled for the possibility that available financial resources positively affected the department's ability to hire high-quality researchers and increase its overall scientific productivity by incentivizing research. We included a variable, bachelor's degrees granted per faculty, to control for teaching load, which might affect departmental-level research productivity. We controlled for incumbents' rank or seniority, using the fraction of associate and full professors to all incumbents at the department level. This variable likely correlates with the average age of the researchers. We also included the moderator variables as controls in all regressions.

In addition, to check the robustness of the results, we included controls that might help rule out potential alternative explanations of the observed relations: the proportion of incumbents with longer organizational tenure to all incumbents, research quality of incumbents, and prior productivity of incumbents. We discuss these controls in more detail when we describe the robustness checks.

Because we have panel data, we used dummy variables for each year to control for possible time-specific effects that affect all chemical engineering departments in the sample, such as market conditions or the general economic environment. In addition, we controlled for unobserved heterogeneity at the department level with department-specific fixed effects. Controlling for fixed effects produced a conservative model, because variation in the dependent and independent variable arose from changes over time within each department (Benner and Tushman 2002). Factors that did not change over time (e.g., hiring policies, reputation) likely affect hiring, quality of hiring, and research performance. Thus, we included both department and year fixed effects in the estimations.

Statistical methods

The dependent variables are count variables and take only nonnegative integer values, so a Poisson regression approach was more appropriate than conventional linear regression models (Greene 2000). However, the variance of the dependent variable exceeded its mean, such that overdispersion might be a concern, suggesting the appeal of a negative binomial regression model that can account for overdispersion (Cameron and Trivedi 1998). To account for both overdispersion and department-specific fixed effects, we thus preferred a fixed effects negative binomial model (Hausman et al. 1984).

EMPIRICAL RESULTS

Table 1 reports the descriptive statistics, including the means, standard deviations, minimum and maximum values, and a correlation matrix among the dependent, independent, and control variables. The average number of papers published annually by a department's incumbent scientists in journals with impact factors of 3 or higher is 8.69. On average, a chemical engineering department in our sample hires 1.79 new scientists every two years, though this value exhibits substantial heterogeneity across years and departments, such that some departments hire very aggressively. The average number of exits is 1.50 faculty members every two years, suggesting an overall expansion of U.S. chemical engineering departments. The pairwise correlations among the independent and control variables are relatively low, so multicollinearity should not be a concern. Inbound mobility, research expertise diversity, and internal collaborative environment are all positively and significantly correlated with the research performance of the incumbents. Yet there is no significant correlation between the share of associate and full professors and the research performance of incumbent scientists.

Insert Table 1 about here

We provide the results in Tables 2–3. The baseline model appears as Model 1, with incumbents' research performance as the dependent variable, measured as total citation-weighted publications. Model 2 builds on the base model by including our combined indicator of inbound mobility, which captures both the average research quality and the number of new entries. The fixed-effects negative binomial regressions show a non-significant effect of inbound mobility on incumbents' research performance. These results are confirmed in Model 3, which uses the same specification as in Model 2, except that the dependent variable is measured as high impact factor publications counts, our second indicator of research performance.

Insert Table 2 about here

In Hypothesis 1, we predicted a stronger positive effect of inbound mobility on the research performance of incumbents with shorter rather than longer organizational tenure. To test this effect, we differentiated shorter and longer tenure incumbents and re-estimated the specification in Models 1–2 for the research performance of each type of incumbents. The dependent variable in Models 4–5 is the research performance of incumbents with shorter tenure, operationalized as total citation-weighted publications. The beta coefficient of inbound mobility is positive and statistically significant in Model 5 ($p < .01$), indicating that inbound mobility has a positive effect on the research performance of incumbents with shorter organizational tenure. We also re-estimated the same model specifications for the research performance of incumbents with longer tenure (see Models 9–10). The beta coefficient of inbound mobility is negative and statistically significant ($p < .10$) in Model 10. To check the robustness of the results, we re-estimated the specifications in Model 5 and Model 10, using the publication counts in high impact journals as proxies for the research performance of short- and long-tenured incumbents; the results are presented in Models 8 and 13, respectively. Whereas the beta coefficient of inbound mobility is positive and statistically significant in Model 8 ($p < .01$), it is negative and significant ($p < .01$) in Model 13. These findings reveal a different pattern of responses to mobility among incumbents with longer tenure. Specifically, external recruiting has a positive effect on the research performance of short-tenured incumbents but a negative effect on the performance of long-tenured incumbents. These results offer empirical support to Hypothesis 1. It is worthwhile to highlight here that our findings only speak to the impact of inbound mobility on the research performance of short- versus long-tenured incumbents; they should not be interpreted as differences in the absolute research performance of the two groups. For a sense of the magnitude of the effects, an average department that moves from no hiring to an average level of inbound mobility would experience a performance increment of 2.3% for short-term incumbents and a decline of 2.5% in the performance of long-tenured incumbents.

However, if a department hired as a result of an expansion policy, we might observe similar patterns in our data, because the number of faculty members with shorter tenures would increase, along with their research performance, when inbound mobility is very high. To rule out this alternative explanation, we controlled for the proportion of long-tenured incumbents (ratio of the number of long-tenured to all incumbent scientists in a department). The regressions appear in Model 6 for short-tenured incumbents and Model 11 for long-tenured incumbents. The results remain unchanged, though the statistical significance of the coefficient of inbound mobility improves slightly. The sign of this additional control variable is in the expected direction. We then ran the model specifications from Models 5 and 10 for the subset of incumbents who are associate and full professors; the results are in Model 7 for short-tenured incumbents and Model 12 for long-tenured incumbents. This procedure keeps the rank or seniority of the faculty members constant and attributes incumbents' susceptibility to peer effects solely to their organizational tenure. Because rank is also likely correlated with the age of the researcher, this robustness check allows us to disentangle the effects due to longer organizational tenure from those attributed to age. The main results remain unchanged.

Insert Table 3 about here

With Model 14, we introduce a department's research diversity as a potential negative moderator of the relationship between inbound mobility and incumbents' research performance, measured as total citation-weighted publications. The negative, significant interaction term across specifications suggests that academic departments that diversify across many research areas of expertise benefit less from external recruiting, in support of Hypothesis 2. Model 17 represents the same specification but uses publications counts in high impact journals as a proxy for incumbents' research performance; the results remain unchanged. Models 15, 16, 18, and 19 provide tests for the positive moderating effect of internal collaborative environment. Whereas the dependent variable, incumbents' research performance, is measured as total citation-weighted publications in Models 15–16, it is operationalized as publication counts in high impact journals in Models 18–19. As we expected, the interaction term between internal collaborative environment and inbound mobility is positive and significant ($p < .05$) in all the specifications. Departments in which faculty members are more inclined to collaborate internally benefit more from inbound mobility, in empirical support of Hypothesis 3.

Insert Figures 1 and 2 about here

Interpreting an interaction term in non-linear models is complex, because its magnitude, sign, and significance can differ across observations (Hoetker 2007). Therefore, we use graphical analysis to provide a more nuanced understanding of the interaction effects in Model 16. We follow past work (Yayavaram and Chen 2015) and plot the average marginal effects of inbound mobility for various values of a department's research expertise diversity with 95% confidence intervals in Figure 1. When all other variables are at their mean values, the average marginal effects of inbound mobility are positive but decreasing for low values of research expertise diversity, whereas they turn negative for very high values of research expertise diversity. This graph provides support for the negative moderation effect predicted in Hypothesis 2.

Similarly, Figure 2 depicts the average marginal effects of inbound mobility for various values of internal collaborative environment, when all other variables are kept at their mean values. Figure 2 illustrates that the average marginal effects of inbound mobility are negative (but not statistically significant) at very low levels of internal collaborative environment, but they turn positive and are increasing for higher values of internal collaborative environment. The confidence intervals show that the average marginal effects of inbound mobility are statistically significant only for high levels of internal collaborative environment, providing only weak support for Hypothesis 3.

Empirical concerns and robustness checks

The study results are in line with our theoretical framework: The interplay of the mechanisms of localized learning and social comparison appear to drive the effect of inbound mobility on incumbents' research performance, and specific contingencies intervene with the intensity of these mechanisms in the context of academia. Our empirical investigation of these mechanisms likely is subject to some limitations that are common to studies of peer effects and social learning though, which Manski (1993, 2000) describes as endogenous, contextual, and correlation effects. We cannot eliminate these potential biases completely, which would require identifying an exogenous shifter of the propensity to hire new scientists or studying inbound mobility in a quasi-experimental setting, but we address these methodological concerns by following current practice in scholarly research (e.g., Bercovitz and Feldman 2008; Tartari et al. 2014).

First, endogenous and unobserved selection effects are potential concerns, in that high performing scientists might self-select into or be attracted to a department with a reputation for conducting high quality research. If so, the best departments would hire the best scientists, and the coefficient of inbound mobility would be biased upward. As we mentioned previously, we addressed this concern at least partially by including department fixed effects in all the model specifications. If the reputation, research performance, and attractiveness of a department remain constant across time, our approach would cancel out this source of bias. Because some unobserved, across-time variations in a department's features could make it more or less attractive to high performing scientists, we also included controls in our main regressions for the research performance of incumbent scientists, using both incumbents' research quality and their prior productivity. Specifically, we operationalized incumbents' research quality as the average impact factor of the journals in which they published in year t. For incumbents' prior productivity, we calculated the average number of citations received per paper published by incumbents in year t. When we included these controls in the estimations of the full models, the results remained largely consistent and confirmed our main findings. Controlling for both incumbents' research quality and their prior productivity in the same regressions did not alter the results either (available on request). As a potential proxy for a department's research intensity (and attractiveness to external scientists), we also considered its patenting activity. Using patent data drawn from the U.S. Patent and Trademark Office regarding each patent filed by any member of the focal departments during 1996–2004, which we aggregated to the department level, we controlled for the department's number of patents in each year; we repeated the same procedure for a five-year window. The main results remained unchanged (available on request). Furthermore, in all regressions, we controlled for R&D intensity at the department level to rule out the alternative explanation that departments with better access to financial resources would be more likely to hire high quality researchers and increase their overall scientific performance.

Second, department fixed effects also could partially address contextual or correlation biases. Recall that we incorporated a two-year time lag for the measure of the dependent variable, after measuring the independent variables and controls in all the model specifications, so our findings do not suffer from simultaneity or reverse causality concerns. Our regressions also account for many time-varying controls. Yet controlling for all potential contextual factors is very difficult, so some residual spurious correlations might bias our coefficients. Still, we are confident in the main findings, because our focus was on the drivers of heterogeneity in the impact of inbound mobility on incumbent scientists. Even if some biases remain in the estimates of the effect of inbound mobility, we have no good reason to believe that those biases correlated with our moderators.

Third, the effect of new hires potentially could mask the replacement of less productive incumbents by more productive newcomers. To deal with this issue, we controlled for the number of exits, number of emeritus professors, and proportion of long-tenured incumbents. Although some replacement effects arose, the main effects remained significant.

DISCUSSION AND CONCLUSION

For academic and research-intensive organizations, the question of whether to recruit productive scientists relates to the extent to which they can (1) increase the department output with their production and (2) generate positive externalities at the organizational level (e.g., boost the productivity of other colleagues, attract research funds, influence further hiring decisions). Prior research demonstrates consistently that knowledge transfer through hiring results mainly from the first channel, that is, the productive role of new recruits and their direct contribution to organizational research output (Singh and Agrawal 2011; Song et al. 2003). Beyond this direct effect, the arrival of new scientists can exert indirect effects (knowledge spillovers, peer effects) on the productivity of incumbent scientists, thereby influencing the organization’s performance output in a more subtle way (Lacetera et al. 2004). This study combines elements from learning theory and social comparison theory to suggest that such effects depend on the local social dynamics between new hires and incumbents and can be explained by the mechanisms of localized learning and social comparison; the intensity of such mechanisms is conditioned by particular contingencies. Our empirical analysis, based on a unique sample of 94 academic departments active in chemical engineering research, provides empirical support for these predictions and adds to existing literature on the role that productive, star scientists play in enhancing others' performance (Azoulay et al. 2010; Lacetera et al. 2004; Oettl 2012; Zucker et al. 2002). Our results complement this body of work by providing boundary conditions of the widely theorized, positive effects of recruiting new scientific personnel on performance by existing employees. Our study also extends current research on peer effects in academia (e.g., Bercovitz and Feldman 2008; Tartari et al. 2014), by studying this phenomenon in the context of inbound scientists' mobility. Thus, our results indicate that, in certain circumstances, hiring new scientists can add to the organizational knowledge base by inducing peer effects on the performance of incumbent scientists.

However, our findings suggest that inbound mobility does not induce a uniform effect on all incumbents. Rather, the arrival of new scientists leads to an increase in performance only for the subgroup of incumbents with shorter tenure in the organization. These findings suggest some clear paths for further investigation; in particular, studies should explore whether scientific recruitment has differential effects on the performance of other subsets of incumbents (e.g., star vs. non-star incumbents, research- vs. teaching-oriented professors). Although we proxy for the quality of new hires by their prior productivity, we are not able to capture their unrealized latent potential; it would be interesting to explore how other features of the new hires (or their former workplaces) affect their impacts, in terms of learning and social comparison.

Academic departments with less diversified expertise and higher levels of internal collaborations among faculty members can reap greater benefits from learning by hiring. These findings in turn have implications for how organizations can capitalize on external expertise and knowledge sourced through hiring for innovation processes. They also are consistent with extant literature pertaining to integrative capabilities and knowledge recombination across organizational boundaries (Kogut and Zander 1992; Rosenkopf and Nerkar 2001; Tzabbar et al. 2013; Zahra and George 2002).

Our findings offer some practical recommendations for managing research-intensive organizations too. For example, the success of an organization's hiring strategy might depend on its ability to retain existing scientists and enhance their productivity. Improving research performance is a slow process that requires sustained hiring for multiple years. Our results show that organizations that historically have not attracted inbound scientists are unlikely to transform their incumbent scientists' research performance through just a one-shot hiring campaign. A department mostly formed by long-tenured faculty sees a (small) negative indirect impact from inbound mobility. In addition, the magnitudes of our estimates suggest that, in general, the effect associated with learning by hiring is small. Renewing an organization's research capabilities requires both time and commitment. To benefit fully from inbound mobility, the organization should attempt to activate internal knowledge sharing and collaboration processes. Our results indicate important complementarities between policies that foster internal collaboration and those that increase inbound mobility. Thus, to improve its research capability, a knowledge-intensive organization should establish a clear, comprehensive strategy, rather than implementing isolated measures.

Although the academic research sector provides an excellent setting to test the implications of our theoretical model, it also exhibits some unique specificities. For example, it is highly institutionalized (Bercovitz and Feldman 2008) and operates according to prevailing norms of open science (Dasgupta and David 1994). Yet gaining insights into how incumbent scientists respond to the arrival of new, productive colleagues has relevance not just for academic units but for research-driven organizations in general. Firms in science-based sectors such as biotechnology often face similar challenges (Lacetera et al. 2004; Tzabbar 2009). However, the potential generalizability of our results to industry settings requires further confirmation in additional studies. This study provides an interesting option for examining the relative effects of hiring productive researchers to organizations, as well as the improvements they bring because of their indirect effects on incumbents.

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Table 1. Descriptive statistics and correlations

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Research performance of incumbents (total citations), year t+2	396.76	537.51	0	5611	1.00													
2	Research performance of incumbents with shorter organizational tenure (total citations), year t+2	100.11	161.56	0	1194	0.71	1.00												
3	Research performance of incumbents with longer organizational tenure (total citations), year t+2	296.65	437.64	0	4772	0.97	0.50	1.00											
4	Research performance of incumbents (number of publications in high impact journals), year t+2	8.69	11.93	0	81	0.92	0.65	0.89	1.00										
5	Research performance of incumbents with shorter organizational tenure (number of publications in high impact journals), year t+2	2.34	3.95	0	38	0.69	0.86	0.53	0.73	1.00									
6	Research performance of incumbents with longer organizational tenure (number of publications in high impact journals), year t+2	6.35	9.44	0	67	0.88	0.46	0.91	0.96	0.50	1.00								
7	Inbound mobility	4.01	4.60	0	32.17	0.29	0.27	0.25	0.32	0.33	0.26	1.00							
8	Department's research expertise diversity	0.89	0.07	0	0.96	0.22	0.21	0.19	0.22	0.20	0.19	0.24	1.00						
9	Internal collaborative environment	0.03	0.03	0	0.18	0.29	0.18	0.29	0.33	0.19	0.33	-0.03	0.05	1.00					
10	Department size	12.93	5.42	3	34	0.39	0.29	0.37	0.38	0.29	0.36	0.26	0.25	-0.05	1.00				
11	Exits (year t, year t-1)	1.50	1.42	0	8	0.17	0.16	0.14	0.15	0.17	0.12	0.34	0.10	-0.11	0.11	1.00			
12	R&D intensity	2.36	1.72	0	10.06	0.31	0.22	0.30	0.34	0.24	0.33	0.16	0.09	0.24	0.13	0.16	1.00		
13	Bachelor's degrees granted per faculty	3.55	1.70	0.45	12.23	-0.04	0.01	-0.06	-0.06	0.01	-0.08	-0.01	0.05	-0.13	0.01	0.19	0.09	1.00	
14	Faculty rank	0.88	0.10	0.50	1	-0.02	-0.12	0.02	-0.05	-0.10	-0.02	0.07	-0.05	-0.08	-0.01	0.02	-0.17	0.04	1.00

Table 2. Results of panel data negative binomial regressions with organizational fixed effects for incumbents' research performance

	Research performance of incumbents , year t+2			Research performance of incumbents with shorter organizational tenure , year t+2					Research performance of incumbents with longer organizational tenure, year t+2				
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Inbound mobility		-0.007	-0.006		0.033 ***	0.036 ***	0.037 ***	0.027 ***		-0.013 *	-0.015 **	-0.013 *	-0.017 ***
		(0.006)	(0.005)		(0.009)	(0.009)	(0.010)	(0.009)		(0.007)	(0.007)	(0.007)	(0.007)
Department size (incumbent scientists)	-0.011	-0.010	-0.034 **	0.054 ***	0.051 ***	0.049 ***	0.027 **	0.014	0.007	0.009	0.010	0.006	-0.031 **
	(0.008)	(0.008)	(0.014)	(0.010)	(0.010)	(0.010)	(0.011)	(0.020)	(0.008)	(0.008)	(0.008)	(0.008)	(0.015)
Exits (year t, year t-1)	-0.007	-0.001	-0.003	0.071 **	0.040	0.048	-0.026	0.041	-0.008	0.002	-0.004	0.003	-0.002
	(0.018)	(0.018)	(0.018)	(0.030)	(0.031)	(0.031)	(0.039)	(0.035)	(0.020)	(0.021)	(0.021)	(0.021)	(0.022)
R&D intensity	0.019	0.019	0.040 *	0.018	0.009	0.002	0.038	0.069	0.003	0.003	0.009	0.010	0.051 **
	(0.019)	(0.019)	(0.022)	(0.030)	(0.030)	(0.030)	(0.036)	(0.045)	(0.021)	(0.021)	(0.021)	(0.021)	(0.025)
Bachelor's degrees granted per faculty	0.004	-0.002	-0.049	0.036	0.051	0.062 *	0.047	-0.097 *	-0.021	-0.028	-0.031	-0.036	-0.069 *
	(0.022)	(0.023)	(0.032)	(0.032)	(0.033)	(0.033)	(0.038)	(0.053)	(0.025)	(0.025)	(0.025)	(0.025)	(0.037)
Faculty rank	-0.436	-0.365	-0.318	-4.143 ***	-4.406 ***	-2.946 ***	0.855	-2.288 ***	0.843 ***	0.960 ***	0.200	1.250 ***	0.657 *
	(0.271)	(0.277)	(0.310)	(0.453)	(0.457)	(0.564)	(0.570)	(0.595)	(0.306)	(0.312)	(0.386)	(0.315)	(0.381)
Department's research expertise diversity	2.800 ***	2.895 ***	0.020	1.517	1.176	0.966	2.276	3.840	2.375 ***	2.555 ***	2.628 ***	2.539 ***	-0.189
	(0.690)	(0.697)	(0.903)	(1.135)	(1.132)	(1.096)	(1.649)	(2.473)	(0.709)	(0.723)	(0.738)	(0.721)	(0.929)
Internal collaborative environment	3.836 ***	3.750 ***	0.440	4.299 ***	4.583 ***	5.328 ***	4.119 **	1.664	4.360 ***	4.191 ***	3.758 ***	4.657 ***	0.487
	(0.930)	(0.931)	(1.107)	(1.557)	(1.559)	(1.555)	(1.890)	(2.174)	(1.059)	(1.060)	(1.068)	(1.059)	(1.344)
Proportion of incumbents with longer tenure						-1.599 ***					0.924 ***		
						(0.364)					(0.275)		
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.534	-0.642	3.572 ***	0.838	1.304	1.410	-4.596 ***	-0.913	-1.768 **	-1.970 ***	-2.038 ***	-2.218 ***	2.550 **
	(0.674)	(0.682)	(0.938)	(1.077)	(1.078)	(1.047)	(1.553)	(2.316)	(0.708)	(0.722)	(0.734)	(0.721)	(0.997)
Number of observations	765	765	744	746	746	746	732	652	765	765	765	765	739
Number of academic units	94	94	90	91	91	91	89	78	94	94	94	94	89
Log likelihood	-3947.84	-3947.09	-1417.56	-2859.82	-2853.57	-2844.39	-2268.70	-900.67	-3778.64	-3776.83	-3770.96	-3754.08	-1282.14
Chi squared	496.31	499.48	374.31	225.09	244.17	261.92	99.15	160.81	323.19	328.70	342.75	334.19	234.90

Standard errors are in parentheses

*p<0.10; **p<0.05; ***p<0.01

Table 3. Results of panel data negative binomial regressions with organizational fixed effects for incumbents' research performance: Moderator effects

	Research performance of incumbents (total citations), year t+2						Research performance of incumbents (number of publications in high impact journals), year t+2					
Variable	Model14		Model15		Model16		Model 17		Model 18		Model 19	
Inbound mobility*Internal collaborative environment			0.391	**	0.385	**			0.406	**	0.381	**
			(0.174)		(0.176)				(0.163)		(0.162)	
Internal collaborative environment			2.527	**	2.483	**			-1.268		-1.055	
			(1.099)		(1.102)				(1.302)		(1.308)	
Inbound mobility* Department's research expertise diversity	-0.601	***			-0.541	***	-0.371	**			-0.360	**
	(0.156)				(0.155)		(0.144)				(0.146)	
Department's research expertise diversity	3.711	***			3.838	***	0.593				0.577	
	(0.782)				(0.792)		(0.999)				(0.998)	
Inbound mobility	0.543	***	-0.019	**	0.474	***	0.334	**	-0.025	***	0.306	**
	(0.143)		(0.009)		(0.143)		(0.131)		(0.009)		(0.134)	
Department size (incumbent scientists)	-0.006		-0.001		-0.004		-0.031	**	-0.037	***	-0.033	**
	(0.008)		(0.008)		(0.008)		(0.013)		(0.014)		(0.014)	
Exits (year t, year t-1)	-0.007		-0.005		-0.003		-0.003		-0.005		-0.004	
	(0.018)		(0.019)		(0.018)		(0.018)		(0.018)		(0.018)	
R&D intensity	0.036	*	0.020		0.028		0.042	*	0.050	**	0.050	**
	(0.019)		(0.019)		(0.019)		(0.022)		(0.022)		(0.022)	
Bachelor's degrees granted per faculty	-0.017		0.007		-0.010		-0.054	*	-0.057	*	-0.062	*
	(0.023)		(0.023)		(0.023)		(0.032)		(0.032)		(0.032)	
Faculty rank	-0.472	*	-0.410		-0.372		-0.328		-0.253		-0.250	
	(0.275)		(0.279)		(0.276)		(0.308)		(0.311)		(0.309)	
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Constant	-1.140		1.921	***	-1.487	*	3.105	***	3.674	***	3.148	***
	(0.753)		(0.307)		(0.766)		(1.007)		(0.438)		(1.016)	
Number of observations	765		766		765		744		745		744	
Number of academic units	94		94		94		90		90		90	
Log likelihood	-3947.98		-3958.32		-3938.01		-1414.46		-1414.58		-1411.57	
Chi squared	495.35		494.48		522.52		387.56		378.15		391.48	

Standard errors are in parentheses
*p<0.10; **p<0.05; ***p<0.01

Figure 1. Average marginal effects of inbound mobility with 95 percent confidence intervals for different values of department's research expertise diversity

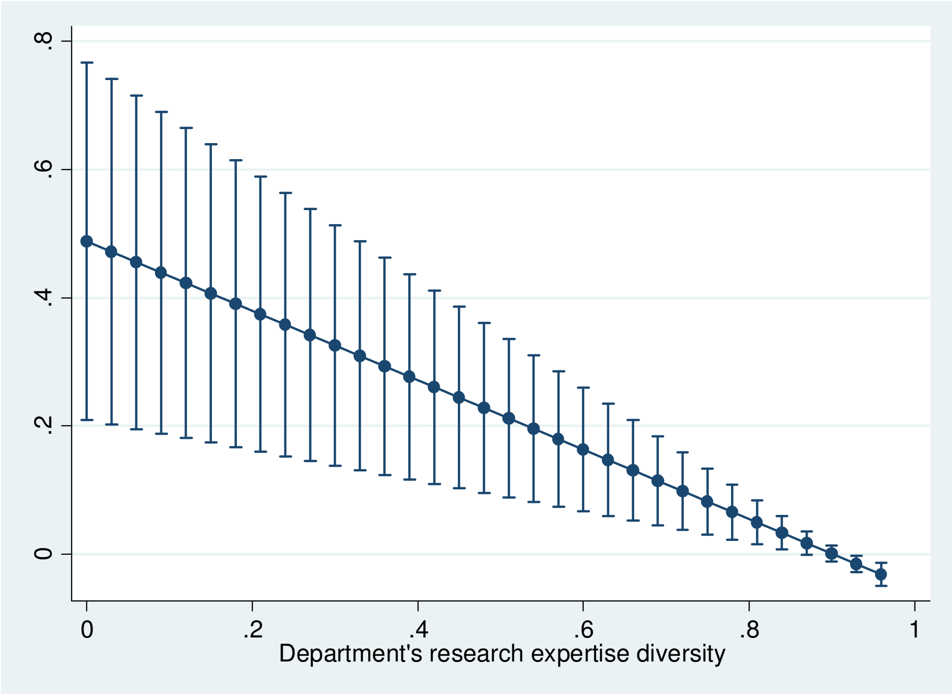

Figure 2. Average marginal effects of inbound mobility with 95 percent confidence intervals for different values of internal collaborative environment