

Manuscript version: Author's Accepted Manuscript

The version presented in WRAP is the author's accepted manuscript and may differ from the published version or Version of Record.

Persistent WRAP URL:

<http://wrap.warwick.ac.uk/106977>

How to cite:

Please refer to published version for the most recent bibliographic citation information. If a published version is known of, the repository item page linked to above, will contain details on accessing it.

Copyright and reuse:

The Warwick Research Archive Portal (WRAP) makes this work by researchers of the University of Warwick available open access under the following conditions.

Copyright © and all moral rights to the version of the paper presented here belong to the individual author(s) and/or other copyright owners. To the extent reasonable and practicable the material made available in WRAP has been checked for eligibility before being made available.

Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge. Provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way.

Publisher's statement:

Please refer to the repository item page, publisher's statement section, for further information.

For more information, please contact the WRAP Team at: wrap@warwick.ac.uk.

LEARNING BY SECONDING: EVIDENCE FROM NSF ROTATORS

Christos Kolympiris
Warwick Business School
University of Warwick
Christos.kolympiris@wbs.ac.uk

Sebastian Hoenen
Rotterdam School of Management
Erasmus University
hoenen@rsm.nl

Peter G. Klein
Hankamer School of Business
Baylor University
Peter_Klein@baylor.edu

Forthcoming Organization Science

Abstract: We study knowledge flows between organizations through secondments, short-term employee assignments at an organization different from the home institution. Secondments allow the sending organization to capture knowledge and network resources from the receiving organization without an organization-level contract, alliance, or co-location, a process we term *learning by seconding*. We focus on the National Science Foundation's rotation program, under which the NSF employs academics, called rotators, on loan from their university, to lead peer reviews. We ask how rotators affect the behavior of their academic colleagues after returning from a secondment. Using difference-in-difference estimations we show that rotators' colleagues raise considerably more research funds than similar scientists who do not have a rotator colleague. Additional quantitative and qualitative evidence implies that the treatment effect occurs via knowledge transfer, as rotators help generate ideas, frame proposals, and explain processes, rather than rent-seeking on the part of the rotator. Overall, the results suggest that strong ties and shared social identity play an important role in organizational knowledge acquisition.

Keywords: secondments, National Science Foundation, rotator, organizational learning, knowledge flows, coarsened exact matching

Acknowledgements

The research reported in the manuscript is part of NSF grant SMA-1548028. An earlier version of this work received the best paper award at the DRUID 2017 conference. We are thankful to the editor and three anonymous reviewers for their feedback and guidance. A special thanks to the Center for Research in Entrepreneurship and Innovation at the University of Bath School of Management (CREI@Bath), in which the first author was a member when conducting this research, for the feedback sessions. We are grateful to Sandra Evans of NSF for processing the FOI request. Maryann Feldman and Jeffrey Mervis sparked our interest in developing the research stream on NSF rotators. We also received valuable insights and support from Janet Bercovitz, Scott Cunningham, Dirk Czarnitzki, Linus Dahlander, Daniela Defazio, Dimo Dimov, Dan Elfenbein, Grigorios Emvalomatis, Virgilio Failla, Aldo Geuna, Matte Hartog, Karin Hoisl, Adam Jaffe, Yujin Kim, Cornelia Lawson, Babis Mainemelis, Doug Miller, Solon Moreira, Elena Novelli, Andreas Panagopoulos, Corey Phelps, Ammon Salter, Markus Simeth, Paula Stephan and Keyvan Vakili. Philipp-Lucas Wahler provided outstanding data collection support.

Introduction

Knowledge acquisition is a key source of competitive advantage. How do organizations acquire knowledge? Arrow (1971) provided a classic answer: individuals and groups become more efficient with experience—they learn by doing (see also Romer 1990; Young 1991). Organizations develop capabilities over time (Penrose 1959) as individuals learn and share that knowledge with colleagues. Tacit knowledge diffuses easily among employees of the same organization because they tend to have strong ties, have similar characteristics, and, as such, share a common social identity (Kane et al. 2005). However, internal knowledge diffusion can be uneven (Dahlander et al. 2016) and, because knowledge is gained on the job from insiders, it is difficult to incorporate new, non-overlapping knowledge into the organization (Molina-Morales and Martínez-Fernández 2009).

But, new knowledge is critical for organizational growth and improvement (Inkpen and Tsang 2005), and organizations may acquire it by hiring workers from organizations already possessing the relevant knowledge, the phenomenon of learning by hiring (Jain 2016; Slavova et al. 2016). As Simon (1991: 125) notes, an organization learns not only “by the learning of its members,” but “by ingesting new members with knowledge the organization didn’t previously have.” New employees bring reputations, network ties, and tacit knowledge acquired from previous work experience. These employees may also model certain behaviors, including ways of learning, that help current employees learn faster and better (March 1991; Slavova et al. 2016). However, new employees typically lack (social) ties with existing employees, are often dissimilar to them, and may appear as outsiders, hindering the transfer of tacit knowledge (Gruenfeld et al. 2000; Hargreaves Heap and Zizzo 2009; Inkpen and Tsang 2005; Phelps et al. 2012), a potential drawback of learning by hiring (Agrawal et al. 2017; Szulanski 2000).

We propose an alternative mechanism for acquiring and incorporating new knowledge without the need to overcome social barriers, what we call *learning by seconding*. Secondment is the practice of sending employees of one organization to short-term assignments in another to learn new practices and procedures, establish new ties, and bring these back to the sending organization (Beyer and

Hannah 2002). Secondment is common among technology companies, law firms, consulting firms, and government agencies. Examples include the US Council of Economic Advisers, composed of academics on short-term leaves from universities, the SEMATECH consortium of scientists in semiconductor firms and the US government (Beyer and Hannah 2002), and the Royal Academy of Engineering's Industrial Secondment scheme in the UK.

We combine insights from the literatures of knowledge transfer, employee mobility and social identity to theorize that *learning by seconding* can be a promising mechanism by which organizations can acquire valuable knowledge, network, and similar resources from other organizations. Seconded employees are insiders (the main advantage of learning by doing and what learning by hiring lacks) who can infuse the home organization with new, non-overlapping knowledge (the main advantage of learning by hiring and what learning by doing lacks). This infusion is possible because unlike existing employees and new hires, returning seconded employees are “double embedded” (Baker and Faulkner 2009; Wang 2015), both in the home institution and in the temporary host organization.

As an employee of the home organization, seconded individuals have ties with non-seconded employees that allow tacit knowledge to transfer within an organization, share similar knowledge bases and a common identity (Reagans et al. 2015; Tortoriello et al. 2012). At the same time, unlike learning by doing, secondments allow the focal individual to fuel her knowledge depository with new knowledge which does not overlap with the knowledge of the non-seconded employees. Seconded employees are embedded in the host organization, giving them access to tacit knowledge about processes, routines, and practices. Because they are also insiders in the home organization, they can pass this new, non-overlapping knowledge to employees who never moved. Seconded employees can also be described as “boundary spanners”—individuals with ties to multiple organizations (the sending and the receiving organization).

Earlier work has established that the presence of boundary spanners increases organizational productivity, partly through effective knowledge transfer (Ancona and Caldwell 1992; Tortoriello et al. 2012; Tushman and Katz 1980). To our knowledge, however, no one has looked systematically at the knowledge flows that can result from secondments. We ask the questions, do secondments facilitate knowledge transfer and, if so, what are the mechanisms?

To study secondments we exploit the rotation program at the National Science Foundation (NSF). Under the rotation program, in place since 1970, NSF employs academics, called rotators, who step out of their academic institution for typically 1 to 2 years to lead the review process and exercise decision makings at the agency as Program Directors (PDs). After their secondment these scientists return to their academic homes armed with experience and unique knowledge of the NSF. As a rotator put it during one of our interviews, “I came back knowing how funding decisions were made, and the various ways the institution works. There’s so much more that goes into how they’re balancing decisions. Knowing this really helped in mentoring junior but also senior faculty.”

Besides being a fertile template to study secondments, the rotation program is important in itself. Knowledge flows in and out of government agencies such as the NSF are particularly relevant for scientific research, both at the societal and individual level (Feldman et al. 2014; Stephan 2012). Existing studies of government’s role in science focus mainly on direct funding (Diamond Jr 1999; Lichtenberg 1987; Muscio et al. 2013). However, as with other sectors such as energy, transportation, and financial services in which government plays a large role, there are many channels other than direct funding for government action to benefit particular organizations, regions, or industries. Knowledge flows through public-private partnerships are one example (Kivleniece and Quelin 2012). Seconding academics to government agencies, as the NSF rotator program is doing, represents a not-yet-studied example.

Following convention, we infer knowledge transfer from changes in output which we measure with increases in NSF funding for rotator’s colleagues and for comparable academics (Argote and Ingram 2000). A key means of acquiring new resources such as research funding is through knowledge transfer from new mobile colleagues (Slavova et al. 2016). Mobility in this sense includes not only moving between universities (Slavova et al. 2016) but also taking temporary editorial positions (Brogaard et al. 2014)¹, the (forced) move of academics from one country to another (Borjas and

¹ Brogaard et al. (2014) examine journal editor rotations, in which an academic takes a temporary position as a journal editor in addition to regular professorial duties. Unlike NSF rotators, journal editors are not seconded; i.e., they a) typically serve longer terms, b) remain working full-time at their home institutions, and c) do not interact face-to-face with other editorial staff located away from the home institution. Brogaard et al. (2014) look

Doran 2012; Waldinger 2010; Waldinger 2012), and academic inbreeding where PhD graduates of a focal university are employed as faculty members in the same academic institution without being employed elsewhere in the meantime (Horta et al. 2010). However, we know surprisingly little about the effects of scientist mobility outside academia such as employment spells in industry or government secondments. These moves are increasingly popular (Geuna 2015) and could prove important in generating knowledge flows towards colleagues as they can equip the focal mobile academic with unique knowledge and insights from outside her core profession, and hence difficult to acquire when mobility is bound to academic circles. And a colleague returning from a stint at a peer or a complementary organization is likely to be viewed as a particularly accessible source of new knowledge.

Our research design takes advantage of the fact that academics within disciplines but across universities are trained in similar ways, have common experiences, and work on similar problems. For this reason, we can compare an NSF rotator's colleagues with academics in the same fields at other universities who do not have a returning rotator in their academic units. As such, our identification strategy features a difference-in-difference estimation in which the dependent variable is the amount of NSF funding for each scientist in academic units (what most universities call departments) with and without a returning rotator. By carefully matching the characteristics of academics with rotator colleagues to those without, we can estimate a treatment effect of bringing an NSF officer back from rotation. Moreover, because rotators typically return to their previous academic institution (hence the decision to return is largely independent to the existing colleagues needing help), we address the endogeneity problem that typically plagues cross-sectional studies of employee mobility (Singh and Agrawal 2011).

at knowledge flows between editors and their current colleagues during the editor rotation (and find a strong effect—the colleagues publish much more in the editor's journal and the papers are high quality, suggesting knowledge transfer rather than favoritism). We look at knowledge transfer between NSF rotators and former colleagues after they return from rotation. Another relevant literature deals with international assignments of employees among subsidiaries of the same multinational corporation (e.g. Criscuolo 2005; Lyles and Salk 1996); because these are internal transfers, however, they do not address non-overlapping knowledge acquisition which is central to our work. Several papers analyze how academics with industry ties impact their colleagues (Bercovitz and Feldman 2008; Stuart and Ding 2006) but do not examine changes in the ability to attract research resources and, unlike our interest, do not study academics who pause their home university duties even temporarily.

The results suggest that secondments do result in knowledge transfer. We find that scientists exposed to their seconded colleague raise considerably more research funding from the NSF when compared to similar scientists in similar academic units who did not have a rotator as a colleague in the *ex-post* period. Using additional empirical tests and a series of interviews, we trace these improvements in funding records to knowledge transfer from the rotator. Based on theories about similarity and strong ties between seconded employees and their colleagues who do not move we identify three main mechanisms: rotators a) help generate ideas by directing colleagues to areas with significant funding opportunities (i.e. *focusing*), b) assist with *framing* proposals in ways they are appealing to reviewers and c) provide processual knowledge by clarifying the instructions and the process of submitting a proposal (i.e. *formatting*).

As with other forms of secondment, acquiring new knowledge that can be transferred back to the originating institution is the main gain of rotation. For this reason, we see these three mechanisms as representative of the more general process of knowledge transfer that underpins secondments. Along the same lines, while the key feature of double embeddedness in the home and the host organization holds across secondments, the NSF rotation setting is a form of secondment that requires the seconded employee to perform tasks that are partially outside her core roles in the home organization. While not all secondments share this feature, it can also be seen in cases such as temporary moves of clinical nurse specialists to university lecturers (Dryden and Rice 2008) and short-term assignments of public sector engineers to small firms (Ho et al. 2016).

Our work makes two main contributions. First, we contribute to the literature on knowledge transfer between and within organizations by means of worker mobility. Departing from the current literature, we theorize that the double embeddedness of the seconded employee in the home and the host organization allows secondments to alleviate some shortcomings of learning by doing and learning by hiring while retaining their advantages. Specifically in the context of academic researchers, prior work has shown that scientists who move within academia bring benefits to their colleagues (Borjas and Doran 2012; Brogaard et al. 2014; Horta et al. 2010; Slavova et al. 2016). By examining secondments, we believe we are the first to study the effects of temporary moves *outside* academia,

then back to the home institution. This is important as it allows for a better understanding of the origins of knowledge acquisition.

Second, we contribute to the literature on inter and intra organization employee mobility (Almeida and Kogut 1999; Argote et al. 2000; Singh and Agrawal 2011; Song et al. 2003; Summers et al. 2012; Tambe and Hitt 2013). By analyzing a hybrid case in which the rotator works outside her institution, and partly outside of her profession, and then moves back to the original institution, we offer new evidence on how employee mobility outside one's core profession can induce gains for colleagues that never moved. Specifically, the knowledge and insights rotators gain during their temporary assignments are different than those gained via moves within academia, because the rotators are exposed to complementary, but not overlapping, knowledge bases while on secondment. More generally, we address the lack of work in the knowledge literature at the micro level (Foss et al. 2010).

Setting: the NSF rotation program

The National Science Foundation supports research in all nonmedical sciences. Each of the seven directorates focuses on a different scientific field: biological sciences, computer and information science, engineering, geosciences, mathematical and physical sciences, social, behavioral, and economic sciences, and education and human resources. The grant process is supervised by Program Directors (PDs), subject-matter experts who oversee the review process. Program directors coordinate with the approximately 40,000 external experts who review proposals, as well as reviewing proposals themselves, chairing review panels, managing program budgets, exercising discretion in making funding decisions, communicating with other PDs, providing formal and informal feedback to applicants, communicating decisions, attending internal and external NSF meetings, and generally navigating the daily internal workings of the NSF (Gorman 2011; McCullough 1994; Muller-Parker 2007; Stephan 2012).

To encourage cross-fertilization, maintain quality control, and increase coordination, PDs also sit in panels in directorates other than their own. As such, they are aware of funding opportunities and the state of scientific progress across directorates. Indeed, during our interviews rotators consistently reported that they spent a substantial amount of their time at NSF on discussing broad issues about various scientific disciplines and how NSF can contribute towards scientific progress.

Since the 1970 passage of the Intergovernmental Personnel Act the NSF has employed academics, called rotators, on loan from their academic institution (rarely from industry) as PDs. These seconded academics serve up to 4 years (typically 1 or 2), working along with permanent NSF PDs (Mervis 2013). Rotators join the NSF to participate in a rigorous and unbiased review system while bringing in fresh ideas and perspectives to the permanent staff (e.g Duce et al. 2012). Before joining the agency as temporary employees, most rotators had received NSF grants, served as *ad hoc* reviewers, and participated on review panels. This experience sparked their interest in the rotation program. As became clear during our interviews the main reasons prompting academics to join the rotation program were a desire to learn more about the NSF and its internal operations and a more general aspiration of having an impact on the profession in part by shaping the direction of science and exercising professional leadership.

In 2016, rotators comprised 28% of the agency's scientific workforce (Mervis 2016a). During their secondments rotators cannot submit a proposal to the NSF, are subject to restrictions when applying for non-NSF funding, cannot review or process proposals of recent collaborators, and in general are subject to strict rules even after their tenures at NSF are over. These restrictions are designed to avoid conflicts of interests and minimize any chances of favoritism in the review process. From 2004 to 2014 the NSF employed nearly 800 rotators from around 400 academic institutions, mostly as PDs. As we discuss later in the paper rotators come from nearly every academic discipline, have diverse backgrounds, vary in their scholarly records, work at small and big universities of different rankings and status, come from every state, and are of different age and gender.

Literature and hypotheses

The transfer of knowledge from one unit of an organization to another is a key input to improvements in organizational performance (Chang et al. 2012). But, the process of knowledge transfer is challenging and often fails (Szulanski 2000). Its success hinges, in large part, on the properties of the knowledge to be transferred and on the relationship between the sender and the recipient of

knowledge (Simon 1991). Specifically, tacit knowledge is more difficult to be transferred than codified knowledge while similarity and strong social ties between the sender and the receiver of knowledge facilitate knowledge transfer (Phelps et al. 2012).

Not surprisingly, learning by doing is a primary means of diffusing knowledge within organizations: as individuals learn, they are interacting regularly with local colleagues, facilitating the flow of tacit knowledge.² Strong ties between group members foster a common social identity in which fellow employees, as insiders, are seen as trustworthy and prone to reciprocity and hence more influential than outsiders (Gruenfeld et al. 2000; Zahra and George 2002). For sourcing tacit knowledge, people tend to rely on those with unique experiences and insights (Gray and Meister 2004) but, because knowledge search processes are often confined locally, co-workers possessing unique knowledge often become the key knowledge source (Borgatti and Cross 2003; Singh 2005; Stuart and Podolny 1996). For these reasons, knowledge transfer among individuals in the same group or subunit is typically more effective than that between individuals in different groups or subunits (Cohen and Levinthal 1990; Tortoriello et al. 2012).

However, while learning by doing facilitates the transfer of tacit knowledge, it is less useful for bringing new, non-overlapping knowledge to the organization. Because new knowledge drives performance improvements (Inkpen and Tsang 2005), organizations often hire workers from outside (Rosenkopf and Almeida 2003). This provides workers of the recipient organization the opportunity to integrate outside knowledge to their current context (Allen 1977), reposition their search processes (Tzabbar 2009), and develop new capabilities that improve performance (Jain 2016). Because knowledge is embedded in individuals and individuals often rely on others' experience to learn (Levitt and March 1988), individuals who move from one context to another can act as knowledge conduits (Argote and Ingram 2000). However, as noted above, new hires lack social ties with incumbents, are often dissimilar, and therefore do not typically share a common social identity with existing employees, hindering the absorption of new tacit knowledge. Indeed, Agrawal et al. (2017) find that hiring a

² Vicarious learning in which employees learn from other employees by observing them is an alternative means of knowledge diffusion. Because vicarious learning does not require direct exchange between the sender and recipient of knowledge (Manz and Sims Jr 1981) we expect it to be less effective at transmitting tacit knowledge.

star employee does not bring noticeable benefits to incumbents. Organizations thus face a trade-off between encouraging internal collaboration, where individuals have a greater ability to learn (from sharing a common social identity), and encouraging external collaboration, where individuals have a greater chance to acquire new, non-overlapping knowledge.

One way to mitigate this trade-off is outward mobility, the practice of sending employees to other organizations while remaining in contact with their former colleagues. Losing valuable employees is generally costly but does provide potential access to the new firm's knowledge and capabilities, as the outwardly mobile employees become insiders in the host organization and acquire new tacit knowledge which they can pass back to their previous coworkers. Importantly, this knowledge is likely to diffuse within the organization because its source is a former insider with ties to other employees sharing a common social identity. Looking at the fashion industry which—like academia—thrives on novelty and creativity, Godart et al. (2014) show that moderate levels of outward mobility are associated with higher levels of creativity inside the sending organization. Wang (2015) finds that skilled immigrants returning to their countries transfer organizational practices to the countries of origin.

We argue that secondments represent an even more valuable form of outward mobility because the movement is temporary. The seconded employee goes to the new organization, acquires new knowledge, and then returns for daily, face-to-face interaction with her former colleagues.³ The main advantage of secondments, we propose, is the double embeddedness of the seconded employees (Baker and Faulkner 2009; Wang 2015). These employees are insiders of both the home (sending) organization and the host (receiving) organization, and this allows them to tap into tacit knowledge acquired by immediate access to routines, decision making processes, and practices that would otherwise be difficult to acquire, and to pass these to their colleagues after returning home. Indeed, because double embeddedness is unique in the case of secondments, there is a need to develop more fine-grained

³ Importantly, while ties between employees ameliorate competitive concerns about sharing knowledge, moves between competing groups within the same organization may exacerbate such concerns (Kachra and White 2008). Secondments are plausibly advantageous in that instance as well because the seconded employee does not move from a competing unit within an organization into another.

arguments on the conditions under which knowledge transfer following seconding is more likely to occur—a task we undertake when we present the moderating factors of the main effect.

The NSF rotation program provides an ideal setting for studying the effects of secondments on the sending organization. Specifically, we expect returning rotators to improve their colleagues' ability to secure research funding by transferring to them tacit knowledge about the funding process that can address their lack of experience and judgment (Borgatti and Cross 2003). Specifically, former rotators can provide a) hints on research areas NSF is keen on funding (what we term *focusing*), b) help with *framing* research proposals in ways that are appealing to reviewers and c) tacit knowledge about the grant process (what we term *formatting*). Hence having a rotator as a colleague should encourage more submissions while also improving the quality of submitted proposals, thus leading to increased funding.

Developing a successful NSF proposal is not easy. As described by Custer et al. (2000), the most frequent challenge is conceptualization and visioning of the project, followed by coordination with collaborators, help from the home institution, budget development, and understanding of NSF guidelines and expectations. Rotators can exploit their NSF experience and address all these challenges. Because rotators have hands-on experience with numerous proposals and applicants from different institutions, they can transmit tacit knowledge on designing and producing a successful application (Muller-Parker 2007). Indeed, as mentioned above, providing leadership is a prime reason for a given academic to become a rotator. We expect this motivation to prompt rotators to be particularly interested in helping their colleagues upon returning.

As an example of focusing, one rotator explained to us that rotators “demystify NSF . . . and generally open the door to opportunities that are outside one's radar.” Another told us he “learned valuable lessons about how NSF communicates intentions about funding priorities.” Referring to the mechanism of framing, another rotator said: “I talked to many colleagues, even when they were outside my field, on general aspects regarding what makes a strong proposal at the NSF.” Another described framing and formatting: “People would show me proposals, say ‘can you tell me what you think? I would say ‘well, maybe you should aim it a little different or maybe you should pick a different program’. I also gave some talks and alerted people to particular programs.”

Faculty with a rotator colleague can increase their odds of getting funding both by writing better proposals and by submitting more proposals. Indeed, obtaining funding is the most frequent topic of discussion in mentoring relationships (Feldman et al. 2010), and such mentoring tends to pay off in terms of increasing funding success rates (Blau et al. 2010). While the relationship and transmission of knowledge from rotators to colleagues is not necessarily a mentor-mentee relationship, there are parallels and as such the abovementioned results strengthen our theoretical expectations. Thus, we advance the following hypothesis:

Hypothesis 1. Faculty members in academic units with a seconded returning rotator will improve their NSF grant acquisition record after the rotator returns from the NSF, compared to similar academics without a rotator colleague.

We expect the relational properties between the sender and the recipient of knowledge about NSF grants to influence the effect of the rotator on the funding records of colleagues (Argote and Ingram 2000; Singh and Agrawal 2011). Relational properties should influence how various colleagues of a returning rotator perceive the rotator's experience, accessibility, and specialized expertise.

As noted above, strong ties between the sender and the receiver improve the transfer of tacit knowledge (Levin and Cross 2004; Simonin 1999). Moreover, strong ties are more likely to develop when the two parties interact over time, as longer relationships help form social cohesion and a common social identity (Kane et al. 2005). Individuals with longer tenure at an organization are more deeply embedded and tend to develop better communication channels with colleagues (Gruenfeld et al. 1996; McFadyen and Cannella 2004; Paruchuri et al. 2006). Those with longer tenure in an institution are also more familiar with organizational routines and practices (Gruenfeld et al. 1996).

In the case of NSF rotators, tenure at the host institution is the prime determinant of the double embeddedness of the seconded employee in the home and the host organizations. While the majority of rotators work at the NSF for approximately 2 years, and therefore the embeddedness at the NSF is nearly fixed, embeddedness at the academic home institution varies widely. Moreover, given our focus on experienced colleagues who might gain from the knowledge held by the seconded employee, the tenure of the seconded employee before rotation also captures tenure overlap between seconded employee and colleagues. This overlap is a good indicator of strong ties which, as noted above, help facil-

itate the transmission of tacit knowledge. Individuals with longer tenure are more likely to be approached for advice that is tailored to the focal environment because they share a common identity with their colleagues, have developed communication channels with them, and are *a priori* expected to provide content-specific feedback. This leads to the following hypothesis:

Hypothesis 2a. The effect of the seconded rotator on the grant acquisition record of her colleagues is positively moderated by her tenure in her academic unit.

A second relational property that should influence knowledge transfer between the rotator and her colleagues is similarity. Even within an academic field there is substantial variation in the specific topics and problems researchers study, the theories and methods they consider appropriate, the journals and communities in which they disseminate their work, and so on (Cole and Cole 1972). Researchers also differ by scientific skill and research productivity: those who are highly productive and whose work is influential will enjoy a strong scholarly reputation, while others will be less well established in their specific fields or in the profession. Both similarity in the specific knowledge base and similarity in research productivity or impact should affect the quantity and quality of knowledge transfer.

As noted above, knowledge transfer is costly both for sender and receiver. The sender must devote time and effort to helping the recipient to understand (Reagans and McEvily 2003), and the recipient must integrate the new knowledge into her knowledge depository. When these costs are lower, senders are more likely to invest time in transmitting knowledge and recipients are more likely to approach senders for help. Importantly, a common knowledge base makes knowledge transfer easier (Black et al. 2004; Reagans and McEvily 2003), so we expect the effectiveness of knowledge transfer between rotators and their academic colleagues to be greater among those working on similar research topics and potentially using similar methods.

Similarity in scientific productivity, influence, and reputation between sender and receiver can also lower the cost of knowledge transfer. More productive individuals have more and newer knowledge and, hence, have more to transmit (Azoulay et al. 2010; Chan et al. 2014; Lacetera et al. 2004; Mas and Moretti 2009). Accordingly, they are more likely to be approached for help. But, they respond differently to different requests (Thomas-Hunt et al. 2003). Experts with similar backgrounds,

capabilities, and experiences are more likely to form strong ties, trust each other, and work together (Gompers et al. 2016; Kretschmer 1997, 1999; Kundra and Kretschmer 1999). For instance, highly accomplished researchers are more likely to connect with other scholars with similar research experience, impact, and reputation who can assimilate the new knowledge (Black et al. 2004; Salomon and Martin 2008). Jha and Welch (2010), for example, find that research collaboration is more common among mature academics who attended the same PhD program. More generally, within organizations, birds of a feather tend to flock together (Tsui et al. 1992). This suggests that returning rotators are more likely to spend time, exchange ideas, and develop close relationships with their more similar colleagues.⁴ This implies that knowledge transfer is facilitated by the sender and receiver being similar in research productivity.

Subsequently, we advance the following two hypotheses:

Hypothesis 2b. The effect of the seconded rotator on the grant acquisition record of a colleague is positively moderated by similarity in knowledge between the rotator and the colleague.

Hypothesis 2c. The effect of the seconded rotator on the grant acquisition record of a colleague is positively moderated by similarity in research productivity between the rotator and the colleague.

Research design and estimation

We use a difference-in-differences research design in which the dependent variable is the inflation-adjusted sum of funds raised by each scientist before and after having a rotator as a colleague. We match “treated” academics with a rotator colleague to similar academics without one. We find matches because academics are not randomly assigned to academic units with and without a rotator colleague. The *ex-post* period is the 5 years after the rotator returns to her academic unit and, equivalently, the *ex-ante* period is the 5 years before the rotator started her tenure at NSF.

⁴ Researchers who are similar to their returning rotator colleagues are likely to be higher in absorptive capacity, reducing the effort needed for them to understand and make use of the knowledge imparted by the rotator. However, because our sample academics, both rotators and colleagues, are very similar in productivity (see Table 2 below), we hypothesize that homophily—strong ties, trust, and similar levels of prior knowledge and skills—is the main driver of knowledge transfer in our context (Cohen and Levinthal 1990; Minbaeva 2007; Podolny 1994).

The research design offers two main advantages. First, selection into rotation is independent of the need of one's colleagues for mentoring on how to raise funds. As already discussed, most academics become rotators because their prior experience at the NSF—serving in discussion panels and communication with the NSF—prompted them to want to learn more about the NSF and its internal operations, not because *ex-ante* they recognize colleagues that need assistance with grant acquisition. Two, where rotators go after the NSF is also independent to existing colleagues. Almost all rotators return to the school where they previously worked. The fact that the return decision is exogenous to the treatment group is important: if the movement of labor to new organizations is endogenous to the anticipated effects of that new labor on existing labor, it is hard to estimate a treatment effect of mobility (Singh and Agrawal 2011).

To make sure the results measure knowledge transfer rather than reciprocal learning (Manski 1993), we include only academics who in the *ex-ante* period had no funds from the NSF. These faculty members have limited (or no) experience in attracting grants and this implies that a) they are less likely to share insights specific to NSF funding with each other and b) they are more likely to gain from the rotator's advice as faculty with established funding records may be of less need (or even desire) for additional help (Laband and Tollison 2000). Accordingly, focusing on this cohort of scientists we expect to be able to unravel the potential effects that rotators may have on the ability of their colleagues to attract research resources.

To build our control sample we use Coarsened Exact Matching (CEM), a multivariate technique that matches on covariate values not exactly, but based on different strata built on the joint distribution of the matching variables.⁵ CEM features a number of desirable statistical properties including the reduction of model dependence, estimation error, and bias (Iacus et al. 2011). In our case, CEM allows us to address heterogeneity at both the level of the individual scientist and the level of her

⁵ Following Iacus et al. (2008) our estimation weights the observations according to the size of the stratum they belong. This is required when, as in our application, the number of control and treatment observations within a stratum are not equal (Blackwell et al. 2009; Iacus et al. 2008). But weighting does not allow us to cluster the standard errors at the observation level. Given that each scientist enters the analysis twice (one in the *ex-ante* period and one in the *ex-post* period) in unreported results we also run the regressions with clustered standard errors at the scientist level without weighting. The results are qualitatively similar to the baseline estimates.

academic unit. We also address heterogeneity at the university level (without using CEM). We build different samples which address different forms of heterogeneity. Specifically, in matching scheme 1 we focus on reducing heterogeneity at the academic unit level, identifying academic units in different universities similar to the academic unit of the rotator based on overlap on science field, faculty size, and average H-index across faculty members *ex-ante*.⁶ We then populate the sample we analyze with a) the faculty members in the academic unit with a rotator without NSF funding in the *ex-ante* period and b) the faculty members in the matched academic units that have also not attracted funds from NSF *ex-ante*.

In matching scheme 2 we use the same matching criteria but match at the individual level, such that members of the same academic unit with a rotator could be matched with scientists belonging to different academic units. For example, assume that the University of Maryland (with a rotator) has professors X, Y, and Z without NSF funding in the *ex-ante* period. Each professor, in this hypothetical scenario, has a single match; professor X's match is at the University of Illinois, professor Y's at the University of Wisconsin, and professor Z's at the University of Florida. Under the individual matching scheme, the matched scientists from Illinois, Wisconsin, and Florida enter the analysis as controls for the three faculty members at Maryland.

Matching scheme 3 combines schemes 1 and 2 to reduce individual-level and academic-unit-level heterogeneity simultaneously. In a nutshell, in matching scheme 3 we first find similar academic units and then find similar scientists only *within* them. Similar to matching scheme 1, the first step in matching scheme 3 is to identify comparable academic units based on science field, average H-index, and faculty size. Within those units, we then match at the scientist level (i.e. matching scheme 2). The

⁶ We expect these factors to influence the accumulation of funds for a given academic as, for instance, some science fields tend to attract more research funds than others. As robustness checks, shown in a later section, we match on different characteristics and find qualitatively similar estimates. On a more technical note, as Singh and Agrawal (2011) explain, with CEM a trade-off must be made between the similarity of the matched sample and the number of observations that are matched. CEM divides variables in bins within certain ranges and then populates the bins with observations that fall within these ranges. Matching observations on variables divided in more bins creates smaller samples that are more similar in the chosen characteristics. The opposite, larger bins, match more observations that are then on average less similar to each other. For matching schemes 1, 2 and 3, we were stricter on science field and H-index by enforcing that every science field gets its own bin and dividing the H-index in 12 bins covering 0 to 75 in increments of 6.81. We determine the *FacultySize* bin boundaries at 30 and 60, effectively creating three bins that represent small, medium and large sized academic units.

key here is that the pool of potential controls for a scientist in an academic unit with a rotator is limited to the scientists of the matched academic unit revealed in the first step. For instance, if the first stage matching reveals that the biochemistry department at the University of Iowa (with a rotator) is similar to the biochemistry department at the University of Missouri (without a rotator), then we do not look for matches for the Iowa scientists outside the Missouri faculty. Specifically, the analysis will include as controls only those academics at Missouri who do not have NSF funds and are close matches to academics without NSF funding *ex-ante* in Iowa. If no match is found among the academics in Missouri (or in Missouri and say the University of Illinois if the latter is also identified as a match to Iowa), then the treatment group academics from Iowa are not included in the analysis.

Finally, in matching scheme 4 we address heterogeneity at the university level (without using CEM) to account for institution-specific incentives, norms, and other factors that can a) condition one's fund raising record and b) potentially prompt a given academic to become a rotator. We select controls who are employed at the rotator's university but in a different academic unit. To choose this unit we imposed two criteria. First, the academic unit must be in the same, immediately larger division or school as the treatment unit. Typically, the immediately larger division was, say, the School of Engineering or the School of Public Policy. In few cases, there were subdivisions within these Schools; there we choose controls from those subdivisions. Two, the control unit must be in a broadly similar scientific field to the treatment unit. For example, the treatment unit is Industrial Engineering, we choose controls from Civil Engineering and not, say, Chemical Engineering.

To identify rotators we first posed a Freedom of Information (FOI) request to the NSF asking for rotator names and affiliations across all agency directorates from 2004 to 2014. We limit our analysis to academics who served as NSF rotators from 2004 to 2009 so that we can observe changes in funding for their colleagues 5 years before and 5 years after rotation. Next, we visited the website of each rotator's academic unit and sourced the list of faculty members including the rotator. For every faculty member we a) collected data from the latest version of her CV, LinkedIn, and other sources, b) downloaded from the bibliographic database SCOPUS a list of her publications over time including co-authors, citations, keywords, and the like and c) recorded her accumulation of NSF funds using data provided online by the NSF.

Using this information, we built a profile of each scientist with a rotator colleague describing her tenure at her institution, research productivity, co-authors, and so on. We sum these profiles to build the profile of each rotator's academic unit. To construct the profile of potential control groups we repeat the steps described above for academic units ranked one position higher and one position lower than the rotator's academic unit in the science-field-specific Shanghai ranking.⁷ Whenever insufficient information was available for these units (usually occurring when the majority of academics in the unit did not maintain an updated professional history online), we moved to academic units two or three ranking positions up and down. We opted for this "one up, one down" approach under the premise that academic units in similar rankings are, at least in broad strokes, comparable to each other. As a final step, the pool of potential matches upon which we implement CEM, for matching schemes 1,2 and 3 contains a) the academics collected via the "one up, one down approach" and b) the scientists belonging to academic units in the rotator's university which, in matching scheme 4, we identified as comparable to the rotator's academic unit. For example, assume that for matching scheme 4 we identify that, within Cornell University, the Materials Science and Engineering Department (with a rotator) is a match to the Physics Department (without a rotator). Then, the Physics Department at Cornell (and its faculty members) enter the pool of potential matches, under matching schemes 1,2 and 3, for academic units with a returning rotator at, say, Carnegie Mellon and Harvard.⁸

To test H1 we interact the variable *Rotator Group* which takes the value of 1 for scientists belonging academic units with a rotator and the variable *Ex-Post* which takes the value of 1 for observations corresponding to the *ex-post* period and 0 otherwise. In support of H1 we expect a positive sign

⁷ For instance, the Texas A&M University's Department of Mathematics, had a rotator returning in 2007. On the Academic Ranking of World Universities, in the field of Natural Sciences and Mathematics in 2007, Texas A&M had a ranking of 43. For this year Georgia Institute of Technology was ranked 42 in Natural Sciences and Mathematics and University of California, Davis was ranked 44. Accordingly, we populate the pool of controls for the Texas A&M Department of Mathematics with academics in the Departments of Mathematics at Georgia Institute of Technology and the University of California, Davis.

⁸ For the example at hand, the fact that we match on science field ensures that the Physics Department at Cornell University (without a rotator) is matched only with Physics Departments hosting a rotator in other universities. Relatedly, the pool of potential control scientists does not include academics who could benefit from a rotator directly: none of the potential control scientists had co-authored a publication with the rotator in the past and none had worked in institutions where the focal rotator had worked before her present academic post. This holds because most rotators had worked only for one university and had collaborated primarily with academics who had won grants themselves.

for the *Ex-Post * Rotator Group* interaction. Following Meyer (1995) we test the moderating effects under H2a, H2b, and H2c using three-way interactions of the *Ex-Post * Rotator Group* interaction and variables we construct to measure tenure and similarity.

We measure tenure (*Tenure*) in the institution as the number of years the rotator has been employed at the focal university. We capture knowledge similarity (*Knowledge Similarity*) by recording the number of top-10 keywords of the rotator's *ex-ante* articles that are also among the top-10 keywords of her focal colleague's *ex-ante* articles. We use the *ex-ante* period under the expectation that the relationships that strengthen knowledge transfer take time to develop.⁹ We measure similarity of research productivity (*Productivity Similarity*) using the absolute value of the difference between the H5-index of the rotator and the H5-index of the focal colleague (multiplied by -1 so that increasing values correspond to higher productivity similarity). The H5-index is a measure of scientific productivity: in the last 5 years, a scientist with an index of h has published h papers, each of which has been cited in other articles h times or more.

In support of H2a, H2b, and H2c we expect positive signs for the three-way interactions *Ex-Post * Rotator Group * Tenure*, *Ex-Post * Rotator Group * Knowledge Similarity*, and *Ex-Post * Rotator Group * Productivity Similarity*. For scientists in the control groups we use the values of the moderators corresponding to academics we estimate to be similar to the rotators (Appendix 1 presents the details of how we identify those individuals). To capture variation in the moderators that is shared among academics in treatment and control groups, and among all observations in the *ex-post* period, we also include in the analysis interactions between *Rotator Group* and the moderators and between *Ex-Post* and the moderators.

In testing our hypotheses, we also include explanatory variables that can affect an academic's ability to get NSF funds. To account for the possibility that other funding crowds out NSF funds we measure the amount of non-NSF funds raised in the *ex-post* period by the focal scientist (*OtherFunds*). We also incorporate a dummy variable taking the value 1 if the academic had attracted funds from the NSF before the *ex-ante* period (*NSFBefore*). To account for potential effects of career experience on

⁹ Because keywords change only slightly throughout our time period, we obtain nearly identical estimates when using the *ex-post* period.

NSF funding we measure the elapsed years from the receipt of an academic's PhD until the start of the *ex-post* period which is the end of the rotation year both for those academics who served at the NSF and for those we identified as "could be rotators" (*Years*). Along the same lines, we include a variable that takes the value of 1 if the focal scientist is assistant professor at the start of the *ex-post* period, 2 if she is associate professor, and 3 if she is full professor (*Position*). Serving in an administrative position may take up time that could be spent in writing grant proposals, so we include a dummy indicator (*Administrator*) that takes the value of 1 for academics who are department heads, PhD studies coordinators, and similar positions at the start of the *ex-post* period. We also include controls for gender (*Male*), scholarly output (*Publications*), and cumulative citations (*Citations*). The latter two variables are time varying as they assume different values for the *ex-ante* and *ex-post* period when the publications and citations record of the focal academic has changed.¹⁰

Academics with extended professional networks may benefit more strongly than others by having a rotator colleague as they have access to larger pool of knowledge and relationships. To account for such effects we include a time-varying variable that counts the number of unique co-authors across time for each focal scientist (*Coauthors*). Scientists in higher-ranked universities may be offered more institutional support when crafting their proposals and may receive a status effect from the NSF, so we include the Shanghai ranking quartile of each academic's university on a given year and field of science (*UniversityQuartile*). The size of one's academic unit may also influence the growth of NSF funds as smaller groups may reflect more intense knowledge flows among faculty members due to elevated familiarity, whereas in larger academic unit the pool of potential knowledge sources is typically larger. We include the number of faculty members in the academic unit (*FacultySize*) to control for these effects. Finally, we include year- and science-field-fixed effects to account for changes in funding trends across years and across scientific fields.

¹⁰ These variables are time-varying which ameliorates concerns of endogeneity arising from the fact that *Citations* and *Publications* are used to construct the *Productivity Similarity* variable. Still, when we omit the variables from the analysis, we reach identical conclusions to the baseline estimates.

Data

Appendix Table 1 describes the data sources and construction of variables we use for the empirical analysis. Appendix Table 2 presents the correlation coefficients for the variables from the sample created with matching scheme 3. To guide the selection of the rotators' academic units we started with the 778 scientists who served as rotators under the Intergovernmental Personnel Act (IPA) program from 2004 to 2014. To fully measure the potential changes in funding for rotators' colleagues in the *ex-post* period we focused on the 203 scientists who worked at the agency from 2004 to 2009 and for a period of up to 2 years (which is the most common length of stay).¹¹ Using the abovementioned data sources we were able to source comprehensive information and build full professional histories for 50 rotators.

We then searched for professional histories of more than 14,000 scientists belonging to a) the 50 academic units with a rotator, b) the approximately 150 academic units ranked one to three positions higher and one to three positions lower than the academic unit with a rotator, and c) the approximately 100 academic units in the same university of the academic unit with a rotator. We succeeded for about a third of these, 5,120, employed at 89 universities reflecting 37 units with a rotator and 160 units without a rotator.¹² Subsequently, we manually read more than 5,000 CVs and went through more than 3,000 LinkedIn pages, 12,000 university and laboratory websites, and 2,000 personal websites. Following this search, we identified 1,515 faculty members in academic units with and without a rotator who met the following criteria: a) their available information was updated and comprehensive enough to build a full professional history (including for instance the PhD graduation date and information on present position), and b) they were in the same academic unit both in the *ex-ante* and in the *ex-post* period. For these 1,515 academics, who compose our original sample, we then downloaded

¹¹ 352 academics served as rotators under IPA from 2004 to 2009 with 203 serving up to two years (the minimum stay for this cohort was 8 months). To illustrate why we limit the search to these 203 scientists, for the rotators whose tenure at the agency lasted 4 years we would have to eliminate those that started rotation in 2007, 2008 and 2009 as the *ex-post* period ends after 2016.

¹² The main reason we could not collect data on the colleagues of 13 rotators was that these scientists were employed at academic units that did not include professional histories on their websites. Importantly, we did not identify significant differences in terms of publication and citation records, NSF funding, age, position, and gender among the 37 academics we use for the analysis and a) the remaining rotators who also served at the NSF during the same period (2004 to 2009) and b) the 778 rotators included in the list coming out of the FOI request.

their more than 110,000 articles included in SCOPUS (including different versions of the first name and searching by university) which were cited by close to 3,000,000 articles to build the *Publications*, *Citations*, *Knowledge Similarity*, *Productivity Similarity*, and *Coauthors* variables.

The distance statistic L1 shows that using CEM has given us control and treatment observations that are more comparable to the original sample than those collected with the one-up, one-down approach. Specifically, the L1 distance between the treatment and control group decreased from 0.754 to 0.629 for matching scheme 1, from 0.641 to 0.619 for matching scheme 2 and from 0.830 to 0.796 for matching scheme 3. Table 1 offers an additional way to check the *ex-ante* comparability of academics in the treatment and control groups. It compares the treatment and control scientists under matching scheme 3, the most restrictive as it addresses heterogeneity both at the scientist and at the academic unit level (descriptive statistics of samples formed with remaining matching schemes are similar).

[Table 1 about here]

Overall, we observe only small differences among the academics in the control and treatment groups. These differences are, for the most part, not statistically significant. For instance, the size of the academic unit for treatment and control groups is on average 33.67 and 33.12 respectively, the number of publications and citations are nearly identical, and so is the presence of females, the tenure of the rotator, and all remaining variables. In sum, the scientists in the control and treatment groups are observationally identical *ex-ante*. Where we do observe significant differences is on the accumulation of NSF funds *ex-post*. Supporting our expectations, academics in groups with a rotator raise on average \$201,505 after the rotator returns to her academic unit while academics in groups without a rotator raise on average \$69,169 during the same period. Note that these sums reflect new grant(s) raised *ex-post* and not continuations or extensions of existing grants.

As shown at the bottom of Table 2, the sample includes rotators from all 7 NSF directorates (and 1 rotator from the office of the Director) with the number of rotators from each directorate being roughly proportional to the funding amounts the focal directorate awards over time. For instance, 21.6 percent of the sample rotators are employed at the Directorate for Mathematical and Physical Sciences,

while over the time period we study this directorate awarded 21 percent of all NSF grants. Note that this proportionality is also reflected in the funding amount received from each Directorate among the sample academics. Compared to their colleagues (including those with NSF funding *ex-ante*) rotators have similar characteristics such as having received their PhD training from institutions of similar ranking but they differ in two main respects. First, in the *ex-ante* period their publication and citation records are below those of their colleagues (e.g. 8.59 versus 23.18 articles). Interestingly, the corresponding figures before the *ex-ante* period are comparable between rotators and their colleagues, with the rotators having somewhat more articles (i.e. 39.97 versus 32.47).

[Table 2 about here]

Taken together, these comparisons suggest that rotators, on average, publish less than they usually do just before joining the NSF. On the other hand, their funding from the NSF is considerably higher than the NSF accumulation of their colleagues both in the *ex-ante* period and before. Therefore, as expected, rotators are typically more successful in raising NSF funds than their colleagues. Similarly, as Table 3 demonstrates, NSF rotators are similar to those we identify as “could-be” rotators. For instance, for both cohorts the elapsed time since PhD graduation until the end of the rotation (and the equivalent period for “could be” rotators) has been 23 years and they are mostly men with H-indices around 9.¹³ In line with the discussion above, the main difference is that the NSF funding records of rotators are higher than the funding records of those academics we have identified as comparable to rotators. As shown in robustness test 7 in Table 8 (below), this difference does not impact our estimates in any material way. Not shown in Table 3, the rotators (and the scientists that match them) are employed at both private and public universities of different size and prestige and from nearly every state. In general, we do not identify trends in terms of the type of institution that rotators come from.

[Table 3 about here]

¹³ The majority of our academics are in the natural sciences, where multiple postdocs are common. On average, having 21 years of experience post PhD at the start of the rotation corresponds to about 13 years since holding a faculty position (i.e., running one’s own lab). Our average faculty member is thus tenured, and about 20% had received NSF funding before the *ex-ante* period (five years before a colleague becomes a rotator). During the *ex-ante* period, when (by construction) none had NSF funding, most had funding from other sources.

Figure 1 plots the average yearly *ex-ante* and *ex-post* funding for rotator colleagues versus scientists employed in the academic units we collected via the one-up, one-down approach. It zooms in on the 431 scientists that did not have NSF grants *ex-ante* (making up our sample), identified using matching scheme 3. While the two groups are similar *ex-ante* (by design), we observe large changes in the *ex-post* period. Figure 1 shows that scientists in the treatment group increase their average funding at a substantially higher rate than scientists in academic units without a rotator. The increase materializes in year 2 and in year 3 after the return of the rotator with year 3 being the pick of the increase.

[Figure 1 about here]

The timing of this increase fits a recurring theme that came up during our interviews: namely, that the rotators helped their colleagues put together their NSF applications in the second and third funding round after their return to their academic unit. In other words, as expected, the rotator effect is pronounced after the rotator has transmitted knowledge for about a year to her colleagues. In line with the interview findings, the decline in funding we observe after year 3 is likely driven by the fact that the majority of academics who were awarded grants in years 2 and 3 did not submit additional applications in years 3 and 4, as they were still working from the earlier grants. Overall, the figure strengthens our expectation of an impact from rotators to their colleagues.

Analysis and results

Table 4 presents the baseline estimates using matching scheme 3, the one we expect to better capture the counterfactual as it is the most restrictive. The results are qualitatively similar when using the other matching schemes (available as Online Appendix Tables 1 to 3). We present 5 specifications. Specification 1 tests the main effect under H1. Then we include separately the moderators we hypothesize in H2a, H2b, and H2c in specifications 2, 3, and 4. Specification 5 is the full specification including all moderators.

[Table 4 about here]

We find strong support for H1 as shown in specification 1. We also fail to reject H2a and H2b while we find only partial support for H2c. The control variables are not statistically significant and do

not change the main results when included, likely because of the matching procedures we have followed which, by design, minimize the differences between control and treatment groups.

Regarding H1, the *Ex-Post * Rotator Group* interaction in specification 1 provides strong support for our theoretical expectation that rotators induce funding improvements for their colleagues. The order of the effect is \$138,367. This figure is significant as it demonstrates that rotators have an effect that is economically meaningful: rotator's colleagues with no NSF funding in the *ex-ante* period raise close to \$140,000 more than similar scientists in similar academic units who do not have a rotator as a colleague in the *ex-post* period. Given that this increase is attributed to the rotator and not to personal characteristics, time-variant factors, or other reasons we conclude that the gains arising from knowledge transfer are material. To put the figure in perspective, as shown in Table 1, we note that in the *ex-post* period academics without NSF funding *ex-ante* belonging to groups without a rotator, raised, on average, \$69,168 from the NSF. These \$69,168 can be attributed to a host of factors such as personal improvements and increased effort but they cannot, by definition, be attributed to the rotator. Still, as our estimates reveal the rotator effect leads to an increase that is twice as large as the increase from all the other potential contributing factors combined.

The estimates in specifications 2 and 5 provide support for H2a. The main rotator effect becomes stronger when the rotator has a longer tenure in her academic unit: the *Tenure*Ex-Post*Rotator Group* variable is statistically significant, while the *Ex-Post*Rotator Group* interaction term ceases to be. Indeed, a one-unit increase in the tenure variable corresponds to an increase of the main rotator effect of around \$13,000. This is consistent with Dahlander and McFarland (2013) who found that even when not working together (i.e. no co-authorship in our case), same-academic-unit colleagues are exposed to each other (and hence can learn from each other). We also fail to reject H2b. When the rotator shares similar knowledge with her colleague the main effect becomes stronger: in specifications 3 and 5 the interaction of the main effect and the *Knowledge Similarity* variable is positive while the level term of the main effect is no longer statistically significant. On the other hand, based on specifications 4 and 5 we find only partial support for H2c; *Productivity Similarity* has a moderating effect on the impact of the rotator only in specification 5. This likely reflects the fact that mature researchers, even

while unsuccessful in previous grant applications, have accumulated enough knowledge and expertise to be successful going forward, even without the assistance of the rotator.

Regarding the managerial implications and generalizability of our results, we conducted several tests to understand better the conditions in which learning by seconding creates value (tables and additional details included in the Online Appendix Tables 4 and 5). We first split the sample according to the length of the secondment to see if this affects knowledge transfer. Consistent with our expectations, we find that longer tenure at NSF appears to give the rotator more knowledge to transmit to colleagues. Next, we looked to see if the nature of the project (here, the grant application) impacts the value of secondments. Specifically, we limited the analysis to scientific fields a) with high rejection rates, b) that evolve fast, and c) which require multidisciplinary approaches. Grant acquisition is potentially more challenging in such fields, so a rotator's insights would be particularly helpful. We find that the rotator effect is indeed stronger in cases b) and c) than in the baseline model (but not for case a)). This shows that the organizations should consider the nature of the project at hand when considering sending an employee on a secondment.

To make sure our quantitative findings are reasonable we conducted a series of telephone interviews in 2016 with 10 rotators and 15 academics (10 without NSF funding *ex-ante* and 5 with funding) employed in academic units with a rotator. The interviews lasted between 15 and 30 minutes. To select these rotators and rotator colleagues we randomly selected rotators who served at the agency between 2009 and 2012 so that they would all have recent experience and recollection with the NSF and with the *ex-post* period. The interviews focused on three main themes: 1) the rotator's experience with the NSF prior to becoming a rotator, her reason for applying to the position and her thoughts on who becomes a rotator, 2) the experience of being a rotator and her position within the NSF, and 3) how returning to the home institution has affected her and her faculty.

As mentioned above, prior experience with the agency lead academics to apply so that they could learn more about the NSF's internal operations. This is particularly relevant because it ameliorates any endogeneity concerns in the empirical analysis as it demonstrates that selection into a rotation position is exogenous to local colleagues needing help in raising funds. It also informs the managerial implications of our work with regards to the value of secondments versus different forms of

knowledge transfer from an external organization such as membership in external committees and government task forces. The scientists at hand had experience with the NSF previously largely by participating in the selection process as an external reviewer. But, such experience did not translate to gains for colleagues. Instead, the secondment in the NSF boosted the colleagues' ability to secure research funding.

All rotators indicated that upon returning to their home institutions, they tried to make their colleagues more knowledgeable about the NSF. Some consulted with the heads of their academic units to identify colleagues working on the NSF's priority issues who could benefit from mentoring. Others assisted faculty members with exploring less-known NSF funding possibilities. Such assistance came from open seminars but also, and more frequently, via one-on-one meetings.

When interviewing rotator colleagues, we refrained from mentioning the rotator but after asking about experience with NSF, we asked if they had ever received help from colleagues with NSF applications. All 5 interviewees who had NSF funds *ex-ante* said they did not receive substantial help from the rotator *ex-post* because they did not need it. The 10 interviewees without NSF funds *ex-ante* identified the rotator as providing valuable assistance in six cases (where, in line with the empirical estimates, there was an overlap in the research topics between the rotator and the focal colleagues). The interviewees mentioned several ways rotators helped them including feedback and direction towards certain funding opportunities. The following is representative of the type of knowledge rotators transfer “[The rotator] organized a day for us to informally talk about opportunities and proposals. He would read the documents we were working on and gave feedback on what could be improved.... [The rotator helped] when trying to figure out what the NSF actually wants to have in a proposal.”

Testing the mechanism and examining alternative explanations

The baseline estimates reported above could reflect not only knowledge transfer, but also political influence—that is, the returning rotator could privately lobby NSF officials on the part of a local colleague, or NSF officials could have an unconscious bias in favor of a former rotator's colleagues. As

shown in Online Appendix Table 6, when we compare the funding records of former and new colleagues of rotators who changed institution after their NSF secondment we do not find evidence of political influence or bias.

If the presence of a rotator in the group in the *ex-post* period coincides with an overall increased focus towards NSF as a funding source at the rotator's academic unit, increased funding records may not reflect learning from the rotator but learning from other faculty members with success in raising funds from the agency. The evidence presented and discussed in Online Appendix Table 7 dismisses such possibility. Similarly, if the rotator's return to her academic unit coincides with rotator colleagues' co-authors or co-investigators having recent success with NSF funding, then our results might be driven by the co-authors or the co-investigators of the rotator colleagues, not the rotator. Online Appendix Table 7 demonstrates that this is not the case.

Because we study increases in funding that take place when the rotator is not in charge of decision making at the NSF and because of the rigorous review system at the agency, we do not expect favoritism to influence our estimates directly. However, it is likely that the rotator's tenure at NSF induces increased visibility of her academic unit. This visibility may cause favoritism for the applications submitted by the rotator's colleagues. We conducted several tests that lead us to discount such a possibility. First, under favoritism we would expect to observe growth in funding among those colleagues that have an established funding record with NSF. As discussed above, we do not find this. Second, under favoritism the grants of rotator's colleagues would be of lower quality than other NSF grants. Measuring quality with publications and citations and exploiting the Google Scholar option to look up grant numbers and link them to publications, we use awards in 2009 across directorates as our template. Table 5 demonstrates that the number of publications and citations coming out of rotator colleagues' 2009 grants are not statistically different than the number of publications and citations coming out of 2009 grants awarded to investigators that do not belong to rotator groups and we collected via the one-up, one-down approach. Third, though this was not part of our research design, none of the academics we analyze submitted a funded proposal in the *ex-post* period jointly with the rotator and, four, none of the rotators co-authored a publication with the sample academics neither *ex-ante* not *ex-post*, which addresses the possibility of "ghost" co-authorship in the funded proposals. Overall, none

of our tests suggest that favoritism explains the increase in funding for rotator's colleagues even indirectly.¹⁴

[Table 5 about here]

The increase in funding we document may be driven by four main mechanisms: a) an increase in the average number of applications submitted per researcher, b) an increase in the average budget per application, c) the submission of different proposals (on different topics) than those that would have otherwise been submitted, and d) the submissions of better or more targeted proposals on the same topics which are more likely to succeed. Because NSF does not provide data on rejected applications on an individual basis we cannot address this directly. But, our interviews did not support mechanism (a). Both rotators and rotator colleagues stressed to us that the amount of time needed to put together a proposal, and the fact that proposals demonstrating ongoing work related to the proposed project have higher chances of success, discourage the submission of multiple applications. Many rotators hinted that most faculty members they interacted with had tried raising funds from the NSF in the past. Said one: "I don't think I had much influence on quantity. Because people were already putting out as much proposals as they could manage, so there wasn't too much room for improvement in that sense." In unreported results we also find econometrically that rotators do not have an effect on the number of awarded grants. Under the premise that more applications correlate with more awarded grants, this reinforces our conclusion that an increase in application does not drive the results.

Online Appendix Table 8 discounts the possibility that option (b) above, an increase in the average size of grants, is driving the results: on average, the grants in our sample are not larger than the population of grants NSF has awarded from 2001 to 2015. While it is difficult to distinguish quality improvements from changes in project or topic, the fact that the *ex-ante* and *ex-post* keywords of articles published by the focal academics overlap almost perfectly (see footnote 9 above referring to the construction of the *Knowledge Similarity* variable) argues against option (c), a switch in topics, as the

¹⁴ In additional tests (not reported here), we compared the popularity of the keywords in articles authored by academics in treatment and control groups to check whether the former group works on "hot topics" which typically attract more funds. We did not find evidence of this effect.

driver of the results because the scientists appear to be working on similar topics in the two time periods. Therefore, in line with the insights from the interviews we conducted and the mechanisms we expect to be at play as captured by the moderators, the effect of the rotator we document appears to stem from direction, feedback and the like on better, more targeted proposals. As one rotator put it, “if somebody has submitted their proposal a couple of times and they’ve been unsuccessful, I can call them up and sort of say ‘Why don’t you show me your reviews and see what they’re telling you.’”

Robustness Checks

Table 6 presents several specifications that test the robustness of the baseline estimates. For ease of exposition we report only the variables that test the hypotheses. To identify faculty members who were in the same academic unit at least 5 years before rotation and 5 years after we relied mainly on the current version of university websites. This could result in missing data as rotator colleagues who left the unit after the rotator returned, but before we collected the information, were likely removed from the unit’s website. We checked this using archival data from the internet archive (<http://archive.org>), which preserves obsolete versions of websites, for all 197 academic units in our sample.¹⁵ As shown in test 1 in Table 6, the results from this analysis are similar to the results in the baseline estimates. As such, we conclude that the potential truncation of the data does not come at any material expense.

[Table 6 about here]

To reduce the heterogeneity among control and treatment groups we have used CEM for academic units outside the rotator’s university and we have found similar academic units in the same university. In robustness checks 2 to 7 in Table 6 we test the findings under alternative ways to reduce heterogeneity. In one approach, used in test 2, we alter the individual-level criteria used as an input to

¹⁵ In total, we retrieved 1,253 faculty members from 123 academic units who left their unit between the fifth year after rotation and 2016. For 35 academic units of the original 197 there was no archived faculty webpage and for 39 there was no change in the faculty members list. Additionally, for almost half of the 123 academic units a proximate period (between 6 and 18 months after the fifth year of rotation) was selected as there was no archived version closer to the required date. Of these 1,253 leaving scientists, 229 from 89 academic units had online accessible work history and matched our selection criteria. An issue with accessing archived faculty webpages is the inconsistency between what is reported in CVs and other online sources, which are generally difficult to source for older dates, and what is shown in, often outdated, websites. Relatedly, as we show in the Online Appendix, similar to Ge et al. (2016) we do not find evidence that only the most productive scientists maintain updated online CVs, LinkedIn pages, and the like.

matching scheme 3 to a) the number of *ex-ante* publications and citations for a given scientist, b) the average number of coauthors one has, as a measure of team orientation, and c) funding level of her academic unit *ex-ante* as measure of inclination to submit grants driven by peer effects. Two, in test 3, we use the academic unit level science field and university quartile as matching criteria. Three, in test 4, we use as controls all academics we have collected data for (and have no NSF funding *ex-ante*) without implementing CEM. Four, in test 5, we use as controls the scientists belonging to the academic units ranked one position higher and one position lower than the academic unit with a rotator. Five, in test 6, instead of matching on faculty characteristics to create the control groups we match solely on rotator characteristics. That is, we first find academics that are similar to rotators based on age, gender, previous NSF funding, and h-index. Then, we include as controls, scientists in their academic units. This exercise relaxes the strict requirements in our baseline estimates under scheme 3 in which we need to identify with precision similar academics in similar academic units and within them discover “could-be rotators.” For the most part, the results we obtain are qualitatively similar to the results of the baseline estimates and as such, they further demonstrate the robustness of our findings.¹⁶

As shown in Table 3 above, the rotators and those academics who match rotators resemble each other in many respects such as having served administrative roles. But, rotators have, on average, higher NSF funding records when compared to the matched group. This difference may bias the estimates of the moderators if rotators and potential rotators are not meaningfully comparable. To test the robustness of our estimates to this potential bias we conducted the analysis using a more comparable

¹⁶ We observe a few differences from the baseline estimates regarding the moderators. We have also checked the assumption of the parallel trend behind the difference-in-difference estimation (Angrist and Pischke 2008). Following previous works (e.g. David 2003) we construct a model where the dependent variable is NSF fund acquisition per year, and include dummy variables for the *ex-ante* and the *ex-post* years in the difference-in-differences estimation (excluding the treatment year). Because the value of the dependent variable is fixed at 0 for the cohort of scientists in the baseline estimates, the focal test employs all the faculty members of a given academic unit in the analysis and not only those that did not raise NSF funds *ex-ante* (the sample we use for the baseline analysis). The interaction terms between the *ex-ante* year dummies and the treatment unit indicator are not statistically significant, which supports the parallel trends assumption. Relatedly, within a 5 year period (the time frame we employ for the analysis) the incentives to fundraising across institutions may change. This would constitute a threat in the analysis as long as there is an interaction between the groups and time period so that changes in incentives, institutional norms and other factors may not influence all groups in the same way. The general homogeneity of the universities and departments in the analysis suggests that this is not an acute concern. Indeed, when we limit our time frame to 2 years, our conclusions remain intact which implies that such potential interaction does not influence our estimation.

set of rotators and potential rotators in terms of funding records. That is, in test 7 in Table 6 we run the baseline specification after we omit from the sample, rotators (and their matching groups) whose funding records exceed 2 million dollars. Once we do so, the average funding records between the two cohorts are more similar: on average, rotators raised \$544,558 *ex-ante* while the corresponding figure for potential rotators is \$436,283 (see Table 3). The results remain qualitative similar to the baseline estimates and our conclusions remain intact.

Discussion and conclusion

We draw on the knowledge transfer, employee mobility, and social identity literatures to suggest that organizations can acquire knowledge as a means of competitive advantage by *learning by seconding*.

To study secondments we exploit the rotation program at the National Science Foundation. Under the rotation program the agency employees, full time, academic scientists for a period of usually 2 years to lead its review process. After we recognize that temporary tenure at the NSF equips seconded scientists with unique knowledge we reveal potentially causal evidence that rotator's colleagues with no NSF funding in the *ex-ante* period raise close to \$140,000 more than scientists who do not have a rotator as a colleague in the *ex-post* period. A battery of empirical exercises as well as interviews with rotators and their colleagues suggest that knowledge transfer and not rent seeking from the side of the rotator is the mechanism behind the effects we reveal. Rotators ignite opportunity recognition, assist with framing proposals and provide processual knowledge (i.e. focusing, framing, formatting). We expect mechanisms of this kind to underpin most secondments because a) one of the main gains of rotation is the acquisition of new knowledge for the seconded employee and b) as with other secondments, NSF rotators become insiders both in the home and in the host organization.

What do these conclusions mean for academic research, for policy as well as for practice? First, they add to our understanding of knowledge transfer. We provide evidence that organizations can learn not only by learning by doing and learning by hiring but also by learning by seconding in large part become secondments offer embeddedness in the host institutions while maintaining embed-

dedness in the home institution. Moreover, we show that similarity and strong ties between the seconded employee and her colleagues make secondments more effective as they strengthen the knowledge transfer between the two parties.

The evidence we provide is far from conclusive and we expect follow-up works to study secondments in more depth. Indeed, a boundary condition of our study is that we analyze a form of secondment that requires stepping out, partially, of one's core duties in the home institution. While such form of secondment is not uncommon, we look forward to future work that analyzes other secondments in which the seconded employee performs similar tasks in the home and the host organization. Further lines of inquiry include analyzing potential drawbacks of secondments and investigating whether learning by seconding is a substitute or complement to learning by hiring and learning by doing. We also add to the literature on employee mobility among researchers and managers as a means of knowledge acquisition (Almeida and Kogut 1999; Singh and Agrawal 2011). This literature has identified conditions that allow organizations to gain from inter-organization employee mobility and have started to gain a better understanding of what makes intra-organization mobility work (Choudhury 2017). But, we lack an understanding of knowledge gains from secondments. Our study sheds light on this neglected theme and therefore starts to address the lack of work in the knowledge literature at the micro level (Foss et al. 2010).

Second, our results speak directly to the literature on the organization of institutions and how they advance or hinder scientific progress (Furman and Stern 2011) as they imply that the design of NSF to employ temporarily but full time university scientists underpins the diffusion of knowledge. It is likely that the knowledge transfer we document here would not have materialized with that magnitude had the review process at the agency been designed in a way that did not include temporary employment of external academics in decision making roles. Therefore, a straightforward implication for our analysis is inquiring whether the NSF design has a differential impact than the design of other agencies which employ academics mainly as reviewers.

Third, we touch upon the literature on science mobility by showing that moves outside academia matter (Borjas and Doran 2015; Brogaard et al. 2014; Waldinger 2010). Our results imply that

for academics temporary moves outside their core academic duties to serve central roles in different types of institutions can afford benefits to the focal academic's colleagues.

Fourth, we highlight the rotation program as a fertile template for studies on the advancement of science, peer effects, knowledge transfer and diffusion, networking, and other topics. We know how scientists, inventors, entrepreneurs, patent examiners and other actors in the knowledge economy affect the rate that science, innovation and entrepreneurship advances. We contend that the centrality of rotators in the knowledge economy (Li and Marrongelle 2013) calls for more scholarly attention to this actor as well. As such, we bring rotators to the forefront in this paper.

For management practice and organizations in general, the implications of our research are straightforward: secondments may be a worthwhile endeavor when seeking to infuse a given organization with new knowledge especially in areas of elevated competition in hopes of improvements in productivity, output and the like. Of course, secondments can be expensive but our analysis suggests that different forms of engagement with an external organization such as membership in external committees do not bring the benefits that secondments do. Rotators were acting as reviewers in selection panels before rotation but their colleagues realized gains in research fund acquisition only after rotation. In fact, we also find that longer rotation periods have stronger effects on knowledge transfer. As well, our study is informative for scientists seeking to raise funds as grant acquisitions records are becoming increasingly more central for tenure decisions, gaining academic status, research performance and overall career progression.

The work also speaks directly to the sources of productivity in science via spillover effects among academics. Keeping in mind that most rotators have had a limited number of career moves, if any, a potentially fruitful means for universities to create spillover effects via scientists with unique experience is to promote NSF rotation within existing faculty members. Still, as it also became clear during our interviews, rotation, for the largest part, comes at the expense of one's own, at least short term, research productivity. Therefore, universities must balance the sorts of benefits we document with the decline in academic productivity that rotation tends to entail.

For policy, our estimates are timely because of the increasing concerns that the expenses of the rotation program should not be covered solely by public funds provided to NSF (Mervis 2016b).

Indeed, a recent policy mandates home universities to bear part of the costs (Mervis 2016a). The basic argument from policy makers is that rotators bring benefits to their home institutions. While our exercise is not meant to provide a cost-benefit analysis, we do document that such benefits in fact exist.

Finally, we look forward to future, qualitative work that explores more deeply what type of knowledge rotators convey, when, to whom and how, under which circumstances, and so on. We conducted interviews to corroborate our findings and provide more insight on context. A larger and more detailed set of interviews would be useful to refine the analysis further. Moreover, if NSF would provide access to rejected applications we could test directly our finding that the estimates we reveal are driven by improvements in the quality and focus of the submitted proposals.

References

- Agrawal, A., J. McHale, A. Oettl. 2017. How stars matter: Recruiting and peer effects in evolutionary biology. *Research Policy* **46**(4) 853-867.
- Allen, T.J. 1977. Managing the flow of technology transfer and the dissemination of technological information within the R&D organization. Cambridge, Mass: MIT Press.
- Almeida, P., B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* **45**(7) 905-917.
- Ancona, D.G., D.F. Caldwell. 1992. Bridging the boundary: External activity and performance in organizational teams. *Administrative science quarterly* 634-665.
- Angrist, J.D., J.-S. Pischke. 2008. *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.
- Argote, L., P. Ingram. 2000. Knowledge Transfer: A Basis for Competitive Advantage in Firms. *Organizational Behavior and Human Decision Processes* **82**(1) 150-169.
- Argote, L., P. Ingram, J.M. Levine, R.L. Moreland. 2000. Knowledge transfer in organizations: Learning from the experience of others. *Organizational behavior and human decision processes* **82**(1) 1-8.
- Arrow, K. 1971. 11 The Economic Implications of Learning by Doing. *Readings in the theory of growth: a selection of papers from the 'Review of Economic Studies'* 131.
- Azoulay, P., J.S.G. Zivin, J. Wang. 2010. Superstar extinction. *The Quarterly Journal of Economics*.
- Baker, W., R.R. Faulkner. 2009. Social capital, double embeddedness, and mechanisms of stability and change. *American Behavioral Scientist* **52**(11) 1531-1555.
- Bercovitz, J., M. Feldman. 2008. Academic entrepreneurs: Organizational change at the individual level. *Organization Science* **19**(1) 69-89.
- Beyer, J.M., D.R. Hannah. 2002. Building on the past: Enacting established personal identities in a new work setting. *Organization Science* **13**(6) 636-652.
- Black, L.J., P.R. Carlile, N.P. Repenning. 2004. A dynamic theory of expertise and occupational boundaries in new technology implementation: Building on Barley's study of CT scanning. *Administrative Science Quarterly* **49**(4) 572-607.
- Blackwell, M., S. Iacus, G. King, G. Porro. 2009. cem: Coarsened exact matching in Stata. *Stata Journal* **9**(4) 524.
- Blau, F.D., J.M. Currie, R.T. Croson, D.K. Ginther. 2010. Can mentoring help female assistant professors? Interim results from a randomized trial. *American Economic Review: Papers & Proceedings* **100**(May) 348 -352.
- Borgatti, S.P., R. Cross. 2003. A relational view of information seeking and learning in social networks. *Management Science* **49**(4) 432-445.
- Borjas, G.J., K.B. Doran. 2012. The collapse of the Soviet Union and the productivity of American mathematicians. *The Quarterly Journal of Economics* 1143-1203.
- Borjas, G.J., K.B. Doran. 2015. Which peers matter? The relative impacts of collaborators, colleagues, and competitors. *Review of Economics and Statistics* **97**(5) 1104-1117.
- Brogaard, J., J. Engelberg, C.A. Parsons. 2014. Networks and productivity: Causal evidence from editor rotations. *Journal of Financial Economics* **111**(1) 251-270.
- Chan, T.Y., J. Li, L. Pierce. 2014. Learning from peers: Knowledge transfer and sales force productivity growth. *Marketing Science* **33**(4) 463-484.
- Chang, Y.-Y., Y. Gong, M.W. Peng. 2012. Expatriate knowledge transfer, subsidiary absorptive capacity, and subsidiary performance. *Academy of Management Journal* **55**(4) 927-948.
- Choudhury, P. 2017. Innovation outcomes in a distributed organization: Intrafirm mobility and access to resources. *Organization Science* **28**(2) 339-354.
- Cohen, W.M., D.A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* **35**(1) 128-152.
- Cole, J.R., S. Cole. 1972. The ortega hypothesis. *Science* **178**(4059) 368-375.
- Criscuolo, P. 2005. On the road again: Researcher mobility inside the R&D network. *Research Policy* **34**(9) 1350-1365.
- Custer, R.L., F. Loepp, G.E. Martin. 2000. NSF funded projects: Perspectives of project leaders. *Journal of Technology Education* **12**(1) 61-74.
- Dahlander, L., D.A. McFarland. 2013. Ties that last tie formation and persistence in research collaborations over time. *Administrative Science Quarterly* **58**(1) 69-110.
- Dahlander, L., S. O'Mahony, D.M. Gann. 2016. One foot in, one foot out: How does individuals' external search breadth affect innovation outcomes? *Strategic Management Journal* **37**(2) 280-302.
- David, H. 2003. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*.

- Diamond Jr, A.M. 1999. Does federal funding "crowd in" private funding of science? *Contemporary Economic Policy* **17**(4) 423.
- Dryden, H., A. Rice. 2008. Using guidelines to support secondment: a personal experience. *Journal of nursing management* **16**(1) 65-71.
- Duce, R.A., K.J. Benoit-Bird, J. Ortiz, R.A. Woodgate, P. Bontempi, M. Delaney, S.D. Gaines, S. Harper, B. Jones, L.D. White. 2012. Myths in funding ocean research at the National Science Foundation. *Eos, Transactions American Geophysical Union* **93**(51) 533-534.
- Feldman, M., P. Desrochers, J. Bercovitz. 2014. Knowledge for the world: A brief history of commercialization at Johns Hopkins University *Building Technology Transfer Within Research Universities: An Entrepreneurial Approach*, 156-191.
- Feldman, M.D., P.A. Arean, S.J. Marshall, M. Lovett, P. O'Sullivan. 2010. Does mentoring matter: results from a survey of faculty mentees at a large health sciences university. *Medical education online* **15**.
- Foss, N.J., K. Husted, S. Michailova. 2010. Governing knowledge sharing in organizations: Levels of analysis, governance mechanisms, and research directions. *Journal of Management studies* **47**(3) 455-482.
- Furman, J.L., S. Stern. 2011. Climbing atop the shoulders of giants: The impact of institutions on cumulative research. *The American Economic Review* **101**(5) 1933-1963.
- Ge, C., K.W. Huang, I.P. Png. 2016. Engineer/scientist careers: Patents, online profiles, and misclassification bias. *Strategic Management Journal* **37**(1) 232-253.
- Geuna, A. 2015. *Global mobility of research scientists: the economics of who goes where and why*. Academic Press.
- Godart, F.C., A.V. Shipilov, K. Claes. 2014. Making the most of the revolving door: The impact of outward personnel mobility networks on organizational creativity. *Organization Science* **25**(2) 377-400.
- Gompers, P.A., V. Mukharlyamov, Y. Xuan. 2016. The cost of friendship. *Journal of Financial Economics* **119**(3) 626-644.
- Gorman, M.E. 2011. Doing science, technology and society in the National Science Foundation. *Science and engineering ethics* **17**(4) 839-849.
- Gray, P.H., D.B. Meister. 2004. Knowledge sourcing effectiveness. *Management Science* **50**(6) 821-834.
- Gruenfeld, D.H., E.A. Mannix, K.Y. Williams, M.A. Neale. 1996. Group composition and decision making: How member familiarity and information distribution affect process and performance. *Organizational behavior and human decision processes* **67**(1) 1-15.
- Gruenfeld, D.H., P.V. Martorana, E.T. Fan. 2000. What do groups learn from their worldliest members? Direct and indirect influence in dynamic teams. *Organizational Behavior and Human Decision Processes* **82**(1) 45-59.
- Hargreaves Heap, S.P., D.J. Zizzo. 2009. The value of groups. *The American Economic Review* **99**(1) 295-323.
- Ho, Y.-P., Y. Ruan, C.-C. Hang, P.-K. Wong. 2016. Technology upgrading of Small-and-Medium-sized Enterprises (SMEs) through a manpower secondment strategy—A mixed-methods study of Singapore's T-Up program. *Technovation* **57** 21-29.
- Horta, H., F.M. Veloso, R. Grediaga. 2010. Navel gazing: Academic inbreeding and scientific productivity. *Management Science* **56**(3) 414-429.
- Iacus, S.M., G. King, G. Porro. 2008. Matching for causal inference without balance checking. *Available at SSRN 1152391*.
- Iacus, S.M., G. King, G. Porro. 2011. Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association* **106**(493) 345-361.
- Inkpen, A.C., E.W.K. Tsang. 2005. Social capital networks, and knowledge transfer. *Academy of Management Review* **30**(1) 146-165.
- Jain, A. 2016. Learning by hiring and change to organizational knowledge: Countering obsolescence as organizations age. *Strategic Management Journal* **37**(8) 1667-1687.
- Jha, Y., E.W. Welch. 2010. Relational mechanisms governing multifaceted collaborative behavior of academic scientists in six fields of science and engineering. *Research Policy* **39**(9) 1174-1184.
- Kachra, A., R.E. White. 2008. Know-how transfer: the role of social, economic/competitive, and firm boundary factors. *Strategic Management Journal* **29**(4) 425-445.
- Kane, A.A., L. Argote, J.M. Levine. 2005. Knowledge transfer between groups via personnel rotation: Effects of social identity and knowledge quality. *Organizational behavior and human decision processes* **96**(1) 56-71.
- Kivleniece, I., B.V. Quelin. 2012. Creating and capturing value in public-private ties: A private actor's perspective. *Academy of Management Review* **37**(2) 272-299.
- Kretschmer, H. 1997. Patterns of behaviour in coauthorship networks of invisible colleges. *Scientometrics* **40**(3) 579-591.
- Kretschmer, H. 1999. A new model of scientific collaboration part 1. Theoretical approach. *Scientometrics* **46**(3) 501-518.

- Kundra, R., H. Kretschmer. 1999. A new model of scientific collaboration part 2. Collaboration patterns in Indian medicine. *Scientometrics* **46**(3) 519-528.
- Laband, D.N., R.D. Tollison. 2000. Intellectual collaboration. *Journal of Political economy* **108**(3) 632-662.
- Lacetera, N., I.M. Cockburn, R. Henderson. 2004. Do firms change capabilities by hiring new people? A study of the adoption of science-based drug discovery. *Advances in strategic management* **21** 133-160.
- Levin, D.Z., R. Cross. 2004. The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer. *Management Science* **50**(11) 1477-1490.
- Levitt, B., J.G. March. 1988. Organizational learning. *Annual review of sociology* 319-340.
- Li, P., K. Marrongelle. 2013. *Having Success with NSF: A Practical Guide*.
- Lichtenberg, F.R. 1987. The effect of government funding on private industrial research and development: a re-assessment. *The Journal of industrial economics* 97-104.
- Lyles, M.A., J.E. Salk. 1996. Knowledge acquisition from foreign parents in international joint ventures: An empirical examination in the Hungarian context. *Journal of international business studies* **27**(5) 877-903.
- Manski, C.F. 1993. Identification of endogenous social effects: The reflection problem. *The review of economic studies* **60**(3) 531-542.
- Manz, C.C., H.P. Sims Jr. 1981. Vicarious learning: The influence of modeling on organizational behavior. *Academy of Management Review* **6**(1) 105-113.
- March, J.G. 1991. Exploration and exploitation in organizational learning. *Organization science* **2**(1) 71-87.
- Mas, A., E. Moretti. 2009. Peers at Work. *The American Economic Review* **99**(1) 112-145.
- McCullough, J. 1994. The role and influence of the US National Science Foundation's program officers in reviewing and awarding grants. *Higher Education* **28**(1) 85-94.
- McFadyen, M.A., A.A. Cannella. 2004. Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships. *Academy of Management Journal* **47**(5) 735-746.
- Mervis, J. 2013. Special Report: Can NSF Put the Right Spin on Rotators? Part 1 *Science*. AAAS.
- Mervis, J. 2016a. To save money, NSF requires university cost-sharing for rotators *Science*. AAAS.
- Mervis, J. 2016b. NSF proposes changes in use of costly rotators for senior positions *Science*. AAAS.
- Meyer, B.D. 1995. Natural and quasi-experiments in economics. *Journal of business & economic statistics* **13**(2) 151-161.
- Minbaeva, D.B. 2007. Knowledge transfer in multinational corporations. *Management international review* **47**(4) 567-593.
- Molina-Morales, F.X., M.T. Martínez-Fernández. 2009. Too much love in the neighborhood can hurt: How an excess of intensity and trust in relationships may produce negative effects on firms. *Strategic Management Journal* **30**(9) 1013-1023.
- Muller-Parker, G. 2007. 'Rotators' in the National Science Foundation's Geosciences Directorate. *Eos, Transactions American Geophysical Union* **88**(18) 200-200.
- Muscio, A., D. Quaglione, G. Vallanti. 2013. Does government funding complement or substitute private research funding to universities? *Research Policy* **42**(1) 63-75.
- Paruchuri, S., A. Nerkar, D.C. Hambrick. 2006. Acquisition integration and productivity losses in the technical core: Disruption of inventors in acquired companies. *Organization Science* **17**(5) 545-562.
- Penrose, E.T. 1959. *The theory of the growth of the firm*. Oxford University Press, New York.
- Phelps, C., R. Heidl, A. Wadhwa. 2012. Knowledge, networks, and knowledge networks: A review and research agenda. *Journal of Management* **38**(4) 1115-1166.
- Podolny, J.M. 1994. Market uncertainty and the social character of economic exchange. *Administrative science quarterly* 458-483.
- Reagans, R., B. McEvily. 2003. Network structure and knowledge transfer: The effects of cohesion and range. *Administrative science Quarterly* **48**(2) 240-267.
- Reagans, R., P.V. Singh, R. Krishnan. 2015. Forgotten third parties: Analyzing the contingent association between unshared third parties, knowledge overlap, and knowledge transfer relationships with outsiders. *Organization Science* **26**(5) 1400-1414.
- Romer, P.M. 1990. Endogenous technological change. *Journal of Political Economy* **98**(5, Part 2) S71-S102.
- Rosenkopf, L., P. Almeida. 2003. Overcoming local search through alliances and mobility. *Management Science* **49**(6) 751-766.
- Salomon, R., X. Martin. 2008. Learning, knowledge transfer, and technology implementation performance: A study of time-to-build in the global semiconductor industry. *Management Science* **54**(7) 1266-1280.
- Simon, H.A. 1991. Bounded rationality and organizational learning. *Organization science* **2**(1) 125-134.
- Simonin, B.L. 1999. Ambiguity and the process of knowledge transfer in strategic alliances. *Strategic management journal* 595-623.
- Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. *Management Science* **51**(5) 756-770.

- Singh, J., A. Agrawal. 2011. Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science* **57**(1) 129-150.
- Slavova, K., A. Fosfuri, J.O. De Castro. 2016. Learning by hiring: the effects of scientists' inbound mobility on research performance in academia. *Organization Science* **27**(1) 72-89.
- Song, J., P. Almeida, G. Wu. 2003. Learning-by-Hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management Science* **49**(4) 351-365.
- Stephan, P.E. 2012. *How economics shapes science*. Harvard University Press Cambridge, MA.
- Stuart, T.E., W.W. Ding. 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences1. *American Journal of Sociology* **112**(1) 97-144.
- Stuart, T.E., J.M. Podolny. 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal* **17**(S1) 21-38.
- Summers, J.K., S.E. Humphrey, G.R. Ferris. 2012. Team member change, flux in coordination, and performance: Effects of strategic core roles, information transfer, and cognitive ability. *Academy of Management Journal* **55**(2) 314-338.
- Szulanski, G. 2000. The process of knowledge transfer: A diachronic analysis of stickiness. *Organizational behavior and human decision processes* **82**(1) 9-27.
- Tambe, P., L.M. Hitt. 2013. Job hopping, information technology spillovers, and productivity growth. *Management Science* **60**(2) 338-355.
- Thomas-Hunt, M.C., T.Y. Ogden, M.A. Neale. 2003. Who's really sharing? Effects of social and expert status on knowledge exchange within groups. *Management Science* **49**(4) 464-477.
- Tortoriello, M., R. Reagans, B. McEvily. 2012. Bridging the knowledge gap: The influence of strong ties, network cohesion, and network range on the transfer of knowledge between organizational units. *Organization Science* **23**(4) 1024-1039.
- Tsui, A.S., T.D. Egan, C.A. O'Reilly III. 1992. Being different: Relational demography and organizational attachment. *Administrative science quarterly* 549-579.
- Tushman, M.L., R. Katz. 1980. External communication and project performance: An investigation into the role of gatekeepers. *Management science* **26**(11) 1071-1085.
- Tzabbar, D. 2009. When does scientist recruitment affect technological repositioning? *Academy of Management Journal* **52**(5) 873-896.
- Waldinger, F. 2010. Quality matters: The expulsion of professors and the consequences for PhD student outcomes in Nazi Germany. *Journal of Political Economy* **118**(4) 787-831.
- Waldinger, F. 2012. Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany. *Review of Economic Studies* **79**(2) 838-861.
- Wang, D. 2015. Activating cross-border brokerage: Interorganizational knowledge transfer through skilled return migration. *Administrative Science Quarterly* **60**(1) 133-176.
- Young, A. 1991. Learning by doing and the dynamic effects of international trade. *The Quarterly Journal of Economics* **106**(2) 369-405.
- Zahra, S.A., G. George. 2002. Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review* **27**(2) 185-203.

Appendix 1

Selection of scientists that could be rotators

To find a potential rotator for every academic unit we have collected data for we run a logistic regression predicting the probability that a given academic in the sample would become a rotator. The sample is composed of all the academics we collected with the “one up, one down” approach. The dependent variable takes the value of 1 for those academics that became rotators and the value of 0 for all remaining academics. The right-hand side variables, also shown in the table below, include *Male*, *Administrator*, *Position*, *Publications*, *Citations*, *Coauthors* and *the sum of NSF funds ex-ante*. For every academic unit we then specify as potential rotator the academic with the highest predicted probability among her colleagues *and* the predicted probability that is closest to the predicted probability of the rotator who belonged to the academic unit one position higher or one position lower in the Shanghai rankings. When the two probabilities are equal for more than one scientist from the same academic unit we implement CEM across faculty members using career age and administrative function as the matching criteria. If, for instance, the pool created via the logistic regression is composed of three scientist, then we specify as the potential rotator the academic with the highest CEM score to the rotator. For 12 control academic units no potential rotator was found mostly because no academic in the unit had the highest score for both predicted probabilities we estimate. As a result, these academic units are omitted from the analysis.

Logistic regression for probability of becoming a rotator.

Variable	Coefficient	Marginal effects
Years	0.008 (.023)	0.000 (.000)
Male	-0.929 (.405)	-0.013 ** (.005)
Administrator	-0.927 (.488)	0.011 (.0004)
Position	0.874 (.327)	-0.001 *** (.000)
Publications	-0.064 (.013)	-0.000 *** (.000)
Citations	-0.022 (.007)	0.005 *** (.001)
Coauthors	0.544 (.162)	-0.008 *** (.01)
<i>NSFsum (millions)</i>	0.072 (.022)	0.000 *** (.000)
Constant	-4.949 (1.102)	0.015 *** (.000)
Wald chi ²		61.92 ***
Observations		1,289
Pseudo R ²		0.2519

** Significant at 5%. *** Significant at 1%. Standard errors in parentheses.

Table 1. Descriptive statistics of scientists in rotator and control academic units.

<i>Matching using scheme 3 (match on academic unit and scientist)</i>							
Variable	# of scientists	Mean	Standard Deviation	# of scientists	Mean	Standard Deviation	Two-sided t-test
<i>NSF funding (ex-ante)</i>	101	-	-	330	-	-	
<i>NSF funding (ex-post)</i>	101	\$201,505.20	\$71,322.21	330	\$69,168.74	\$14,092.56	-2.84 ***
<i>Knowledge Similarity</i>	101	0.22	0.61	330	0.49	1.41	1.97 **
<i>Productivity Similarity</i>	101	48.01	105.65	330	57.59	99.17	1.60
<i>Tenure</i>	101	17.41	7.72	330	18.81	9.61	1.81
<i>OtherFunds</i>	101	0.15	0.36	330	0.16	0.37	-0.05
<i>NSFBefore</i>	101	0.44	0.50	330	0.36	0.48	-1.81
<i>Years</i>	101	22.65	9.35	330	22.22	9.31	-0.30
<i>Position</i>	101	2.82	0.55	330	2.69	0.56	-2.77 ***
<i>Administrator</i>	101	0.37	0.49	330	0.35	0.48	-1.39
<i>Male</i>	101	0.87	0.34	330	0.86	0.35	-0.22
<i>Publications</i>	101	15.48	15.24	330	15.60	15.68	-0.21
<i>Citations</i>	101	26.51	34.14	330	25.54	35.89	0.34
<i>Coauthors</i>	101	1.35	0.85	330	1.47	1.16	0.31
<i>UniversityQuartile</i>	101	2.44	1.08	330	2.32	1.05	-1.27
<i>FacultySize</i>	101	33.67	18.51	330	33.12	13.87	-0.57

** Significant at 5%. *** Significant at 1%.

Table 2. Ex-ante characteristics of the 37 rotators that enter the analysis and their 247 colleagues.

Variable	Rotator averages	Rotator colleagues averages
<i>NSF funding as PI (5 years ex-ante)</i>	\$ 714,180	\$ 302,485
<i>Years</i>	23.43	21.05
<i>Male</i>	0.70	0.87
<i>Position</i>	2.92	2.74
<i>Publications (all years before ex-ante)</i>	39.97	32.47
<i>Publications (5 years ex-ante)</i>	8.59	23.18
<i>Citations (all years before ex-ante)</i>	27.00	43.00
<i>Citations (5 years ex-ante)</i>	17.59	22.31
<i>Coauthors (all years before ex-ante)</i>	1.24	1.08
<i>Coauthors (5 years ex-ante)</i>	3.13	1.50
<i>Administrator</i>	0.27	0.38
<i>Ph.D. from Ivy League</i>	0.08	0.11
<i>Ph.D. from Association of American Universities</i>	0.78	0.71

9 rotators were employed in the Biological Sciences Directorate, 3 in the Computer and Information Science and Engineering Directorate, 4 in the Education and Human Resources Directorate, 5 in the Engineering Directorate, 4 in the Geosciences Directorate, 8 in the Mathematical and Physical Sciences Directorate, 1 in the Office of the Director and 3 in the Social, Behaviour and Economic Sciences Directorate.

Table 3. Ex-ante characteristics of rotators and academics we identified as 'could-be' rotators.

Variable	37 rotators		148 could-be rotators		Two sides t-test
	Mean	Standard Deviation	Mean	Standard Deviation	
<i>NSF funding as PI (ex-ante)</i>	\$ 714,180	\$ 1,044,847	\$ 436,283	\$ 1,115,223	2.44 **
<i>H5-Index</i>	8.59	5.69	8.44	8.61	0.10
<i>Years</i>	23.43	8.55	23.69	8.61	-0.16
<i>Male</i>	0.70	0.46	0.75	0.43	-0.62
<i>Position</i>	2.92	0.60	2.85	0.67	0.58
<i>Publications (all years before ex-ante)</i>	39.97	23.49	25.94	31.39	2.54 **
<i>Publications</i>	8.59	5.69	17.16	22.92	-2.25 **
<i>Citations</i>	17.59	15.39	28.01	35.09	-1.76
<i>Coauthors</i>	3.13	1.88	1.92	1.75	3.37 ***

** Significant at 5%. *** Significant at 1%.

Table 4. Baseline Estimates under matching scheme 3 (specify as control scientists those that are similar to scientists in the rotator academic unit and belong to academic units that are similar to the academic unit of the rotator). The dependent variable is the sum of funds raised from NSF in the *ex-post* period.

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
<i>Ex-Post</i>	61,215.83*** (23,385.57)	46,076.37 (50,700.08)	58,341.34** (24,153.16)	59,184.90** (25,589.33)	39,775.60 (51,907.56)
<i>Rotator Group</i>	-164.24 (33,420.29)	-22,669.17 (82,256.64)	145.46 (35,038.00)	2571.75 (37,026.15)	-25,889.81 (82,026.47)
<i>Ex-Post * Rotator Group</i>	138,366.83*** (46,871.95)	-72,739.79 (112,825.91)	95,064.97 (49,440.90)	167,193.10*** (52,642.87)	-71,533.25 (112,786.37)
<i>Tenure</i>		-1,131.83 (1,758.97)			-1,255.12 (1,749.44)
<i>Ex-Post * Tenure</i>		824.84 (2,362.40)			934.05 (2,346.22)
<i>Tenure * Rotator Group</i>		1,157.72 (4,249.59)			1,394.94 (4,283.18)
<i>Tenure * Ex-Post * Rotator Group</i>		12,196.76** (5,790.87)			12,484.45** (5,884.43)
<i>Knowledge Similarity</i>			-712.30 (13,566.48)		-437.25 (13,515.37)
<i>Knowledge Similarity * Ex-Post</i>			9,734.49 (18,777.92)		10,121.41 (18,710.96)
<i>Knowledge Similarity * Rotator Group</i>			-3,632.05 (49,597.33)		624.47 (49,700.36)
<i>Knowledge Similarity * Ex-Post * Rotator Group</i>			237,768.11*** (78,549.25)		222,621.14*** (78,799.12)
<i>Productivity Similarity</i>				18.67 (141.66)	38.05 (140.14)
<i>Productivity Similarity * Ex-Post</i>				15.12 (152.02)	-0.26 (150.38)
<i>Productivity Similarity * Rotator Group</i>				-54.49 (310.06)	-27.44 (309.82)
<i>Productivity Similarity * Ex-Post * Rotator Group</i>				689.29 (-521.79)	1,117.43** (-525.84)
<i>OtherFunds</i>	-4,368.13 (29,270.10)	-1,154.53 (29,179.30)	859.53 (29,183.17)	-6,395.28 (29,329.61)	1,331.40 (29,110.74)
<i>NSFBefore</i>	39,250.10 (22,444.74)	32,846.69 (22,540.64)	32,121.13 (22,501.93)	40,073.87 (22,479.21)	26,766.77 (22,574.85)
<i>Years</i>	-1,454.01 (1,323.88)	-1,508.16 (1,319.73)	-1,355.11 (1,315.93)	-1,349.41 (1,333.80)	-1,290.27 (1,320.26)
<i>Position</i>	7,586.40 (22,024.77)	7,369.55 (21,930.20)	8,768.79 (21,875.22)	8,456.79 (22,105.47)	9,978.98 (21,839.12)
<i>Administrator</i>	-17,491.30 (21,200.39)	-19,191.22 (21,135.43)	-17,604.94 (21,131.77)	-16,866.21 (21,455.36)	-18,999.43 (21,281.32)
<i>Male</i>	13,190.31 (34,510.71)	20,240.76 (34,495.07)	12,826.91 (34,265.10)	6,388.30 (34,842.30)	10,447.99 (34,498.95)
<i>Publications</i>	316.46 (611.46)	135.50 (614.10)	295.66 (606.92)	371.69 (631.51)	159.00 (627.80)
<i>Citations</i>	-18.36 (430.25)	11.48 (429.16)	20.21 (427.27)	-10.68 (433.49)	58.21 (428.96)
<i>CoAuthors</i>	11,185.30 (8,422.43)	10,928.41 (8,398.03)	10,182.64 (8,393.28)	11,928.50 (8,451.32)	10,951.04 (8390.11)
<i>UniversityQuartile</i>	-10,841.25 (11,935.01)	-6,140.08 (12,189.61)	-8,551.61 (11,877.99)	-11,369.89 (11,996.17)	-4573.93 (12,165.38)
<i>FacultySize</i>	78.26 (633.43)	375.38 (647.80)	224.23 (632.19)	110.72 (642.37)	572.99 (654.13)
<i>Constant</i>	72,524.20 (98,343.94)	86,816.42 (104,360.36)	62,442.90 (97,906.03)	-72,664.21 (124,621.59)	78,799.10 (103,940.76)
Year- fixed effects included	Yes	Yes	Yes	Yes	Yes
Science field fixed effects included	Yes	Yes	Yes	Yes	Yes
Observations	862	862	862	862	862
Adjusted R ²	0.048	0.056	0.054	0.047	0.066
F-test for overall model significance	2.67	2.71	2.65	2.41	2.59

Standard errors in parentheses

*** p<0.01, ** p<0.05

Table 5. Ex-post outcomes of all 2009 NSF awards granted to academics in rotator and control academic units.

Variable	Grants of scientists in academic units with a rotator		Grants of scientists in academic units without a rotator		Two-sides t-test
	Mean	Standard Deviation	Mean	Standard Deviation	
<i>Publications</i>	6.04	0.76	6.83	0.75	0.68
<i>Citations</i>	95.17	18.74	96.55	15.26	0.06

Table 6. Testing the robustness of the baseline estimates

Test #	(1) ¹		(2) ¹		(3) ¹		(4) ¹	
	No Moderators	With moderators	No Moderators	With moderators	No Moderators	With moderators	No Moderators	With moderators
<i>Ex-Post * Rotator Group</i>	133,213.20*** (45,854.91)	-57,081.46 (97,881.46)	111,862.63*** (38,096.03)	-90,655.29 (88,622.06)	143,860.02*** (33,530.84)	-35,434.54 (77,900.36)	107,032.60*** (33,284.88)	-33,308.99 (78,754.69)
<i>Tenure * Ex-Post * Rotator Group</i>		10,507.94** (5,032.77)		13,208.62*** (4,674.49)		10,718.93*** (4,129.08)		7,550.95 (3,898.09)
<i>Knowledge Similarity * Ex-Post * Rotator Group</i>		221,666.00*** (72,511.73)		200,405.03*** (72,808.04)		220,197.14*** (60,506.08)		235,665.63*** (63,324.90)
<i>Productivity Similarity * Ex-Post * Rotator Group</i>		634.10** (-310.95)		888.54** (-360.93)		653.35** (-273.85)		505.27 (-276.67)
Level terms and two-way interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Science field fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,148	1,148	1,188	1,188	1,155	1,155	1,438	1,438
Adj. R ²	0.047	0.065	0.070	0.092	0.063	0.096	0.051	0.071
F	2.69***	3.01***	4.41***	4.15***	4.11***	4.30***	3.96***	3.90***

¹ (1) Adding additional observations from archive.org, (2) academic units matched on departmental NSF funding and individual publications, (3) academic units matched on science field and university, (4) Using all academics (without NSF funding *ex-ante*) as controls without implementing CEM.

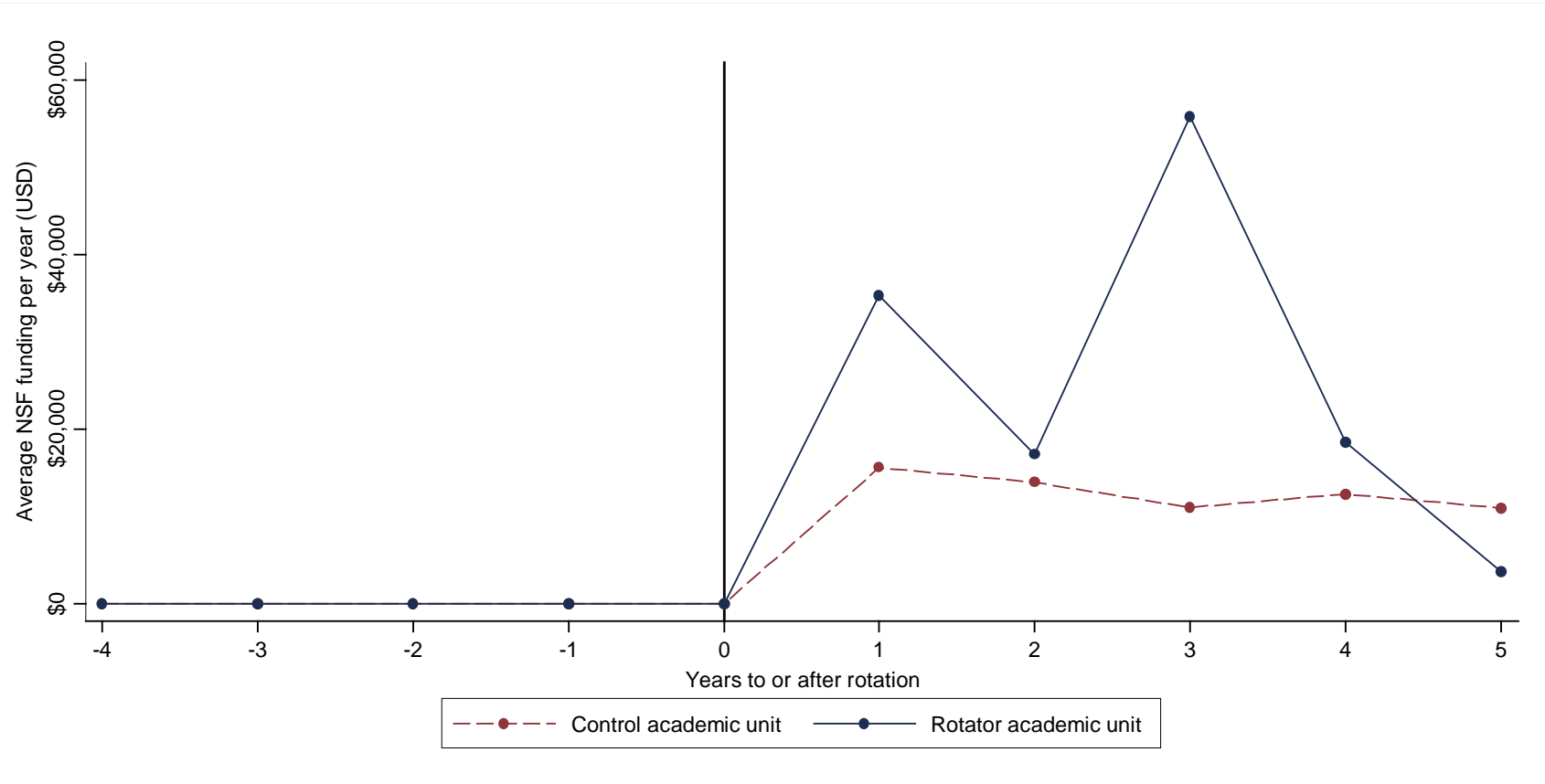
** Significant at 5%. *** Significant at 1%. Standard errors in parentheses.

Table 6 Continued. Testing the robustness of the baseline estimates

	(5) ¹		(6) ¹		(7) ¹	
	No Moderators	With moderators	No Moderators	With moderators	No Moderators	With moderators
<i>Ex-Post * Rotator Group</i>	93,708.35*** (34,678.24)	-80,341.14 (89,377.12)	120,546.43** (46,697.82)	-68,310.90 (119,775.44)	162,584.60*** (52,950.21)	-71,950.57 (126,841.83)
<i>Tenure * Ex-Post * Rotator Group</i>		11,244.17** (4,741.38)		9,834.10 (5,776.02)		13,161.13** (6,626.85)
<i>Knowledge Similarity * Ex-Post * Rotator Group</i>		228,600.45*** (70,048.38)		185,193.62** (76,315.53)		280,277.84*** (89,775.23)
<i>Productivity Similarity * Ex-Post * Rotator Group</i>		667.72** (-315.24)		446.72 (-377.89)		1,065.40 (-568.43)
Level terms and two-way interactions	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Science field fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,378	1,378	736	736	716	716
Adj. R ²	0.064	0.085	0.047	0.060	0.054	0.077
F	4.79***	3.92***	2.38***	2.24***	2.57***	2.63***

¹ (5) Using all academics (without NSF funding *ex-ante*) in academic units ranked one position higher and one position lower than the rotator academic unit as controls, (6) controls chosen based on matched rotator characteristics, (7) omit from the sample rotators (and their matching groups) whose funding records exceed 2 million dollars.

** Significant at 5%. *** Significant at 1%. Standard errors in parentheses.



Appendix Table 1. Details on the construction of selected variables

Variable Code	Description	Construction
<i>Dependent Variable</i>	Sum of NSF funding. Does not include grant extensions of continuations.	We first look up last names of faculty members at the NSF grant database (https://www.nsf.gov/awardsearch/download.jsp). Then, using first name(s) and institution records, the correct person ID is identified manually. Finally, the sum of NSF funds in the specific periods is calculated.
<i>Tenure</i>	Number of years rotator has been part of the focal academic unit.	Biographical information about the rotator is collected from university, laboratory, personal websites, and LinkedIn.
<i>Knowledge Similarity</i>	Number of top-10 keywords of the rotator's <i>ex-ante</i> articles that are also among the top-10 keywords of focal colleague's <i>ex-ante</i> articles	For every rotator and academic in our database, we collect the keywords from all articles published in the <i>ex-ante</i> period. Then, we identify the ten keywords that occur the most in the <i>ex-ante</i> period for every individual. Finally, we count the number of keywords for every academic that his rotator has in his top-10 keywords as well.
<i>Productivity Similarity</i>	Absolute value of the difference between the H5-index of the rotator and H5-index of the focal colleague, multiplied by -1.	For every rotator and academic in our database, we calculate their H5-index in the year the rotator returns to the focal academic unit. Then, we subtract the H5-index of the focal academic from the rotator's H5-index and take the absolute value and multiply it with -1.
<i>OtherFunds</i>	Sum of funding received in the <i>ex-ante</i> or <i>ex-post</i> period not from NSF.	Funding history is collected manually from CVs originating from university, laboratory, personal websites, and LinkedIn. Additionally, National Institutes of Health records were cross-examined with our observations.
<i>NSFBefore</i>	Sum of NSF funding received before the <i>ex-ante</i> period.	For each identified faculty member, we calculate the sum of NSF funding before the year of rotation.
<i>Years</i>	Number of years between receipt of an academic's PhD and the first year of rotation.	We collect the year of receipt of an academic's PhD from CVs originating from university, laboratory, and personal websites and LinkedIn.
<i>Position</i>	Takes the value of 1 if the focal scientist is assistant professor at the start of the <i>ex-post</i> period, 2 if associate professor, 3 if full professor, 4 if distinguished or named professor.	We collect the position of the scientist from CVs originating from university, laboratory, and personal websites and LinkedIn.
<i>Administrator</i>	Takes the value of 1 if the focal scientist served as department chair, dean, or college (vice-) president in the <i>ex-ante</i> or <i>ex-post</i> period.	We collect the scientist's professional history from CVs originating from university, laboratory, personal websites and LinkedIn.
<i>Publications</i>	Number of SCOPUS listed publications for the focal scientist in the <i>ex-ante</i> or <i>ex-post</i> period.	All the SCOPUS indexed publications of the focal scientist are downloaded manually. Then, a script is used to count the number of publications made in the <i>ex-ante</i> or <i>ex-post</i> period.
<i>Citations</i>	Average number of citations per publication for the focal scientist in the <i>ex-ante</i> or <i>ex-post</i> period.	All the SCOPUS indexed publications of the focal scientist are downloaded manually. Then, a script is used to calculate the average number of citations made to the publications in the <i>ex-ante</i> or <i>ex-post</i> period.
<i>CoAuthors</i>	Average number of unique authors per publication of the focal scientist in the <i>ex-ante</i> or <i>ex-post</i> period.	All the SCOPUS indexed publications of the focal scientist are downloaded manually. Then, every co-author of each publication in the <i>ex-ante</i> or <i>ex-post</i> period is counted and the sum divided against the number of publications.
<i>University Quartile</i>	Takes the value of 1 if the university is ranked in the first Shanghai ranking quartile for the specific field and year of rotation, 2 if the university is ranked in the second quartile, 3 if the university is ranked in the third quartile, and 4 if the university is ranked in the lowest quartile for the specific field and year of rotation.	For each specific science field and year of rotation, the Shanghai ranking of the universities is configured into quartiles.
<i>FacultySize</i>	Number of faculty members in the academic unit.	The websites of the academic units in the sample are visited and the number of faculty members that are not in adjunct or emeritus positions is counted.
<i>Science Field</i>	Dummy variable for the scientific field of each focal scientist's academic unit	For each academic unit we measure the number of NSF awards from each Directorate over time. The 7 Directorates are Biological Sciences, Computer & Information Science, Education & Human Resources, Engineering, Geosciences, Mathematical & Physical Sciences, Social, Behavioral & Economic Sciences. We determine the science field (and include associated dummy variables) by identifying the Directorate that has awarded the most grants to the focal academic unit.

Appendix Table 2. Correlation table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
<i>NSF Grant (1)</i>	1.00																
<i>Ex-Post (2)</i>	0.17	1.00															
<i>Rotator Group (3)</i>	0.09	-0.01	1.00														
<i>Tenure (4)</i>	0.03	0.00	-0.06	1.00													
<i>Knowledge Similarity (5)</i>	0.02	0.00	-0.09	0.04	1.00												
<i>Productivity Similarity (6)</i>	0.01	-0.04	0.06	0.04	0.04	1.00											
<i>OtherFunds (7)</i>	-0.02	-0.02	0.00	0.04	-0.07	-0.03	1.00										
<i>NSFBefore (8)</i>	0.10	0.00	0.06	-0.06	-0.07	0.02	-0.08	1.00									
<i>Years (9)</i>	-0.02	0.00	0.01	0.12	0.00	0.06	-0.17	0.07	1.00								
<i>Position (10)</i>	0.03	0.01	0.09	0.03	-0.06	0.07	-0.11	0.15	0.53	1.00							
<i>Administrator (11)</i>	-0.02	0.04	0.05	-0.02	0.06	-0.05	0.10	-0.04	0.08	0.17	1.00						
<i>Male (12)</i>	0.01	0.01	0.01	-0.07	-0.02	0.01	-0.10	0.04	0.13	0.17	-0.02	1.00					
<i>Publications (13)</i>	0.08	0.06	0.01	0.07	-0.01	0.09	0.01	0.11	-0.04	0.13	0.07	0.02	1.00				
<i>Citations (14)</i>	-0.04	-0.23	-0.01	0.07	0.04	0.02	0.03	0.06	0.00	-0.04	-0.01	0.00	0.05	1.00			
<i>CoAuthors (15)</i>	0.05	0.06	-0.01	0.02	0.11	0.01	0.08	0.09	-0.04	-0.07	0.02	-0.06	-0.01	0.24	1.00		
<i>UniversityQuartile (16)</i>	-0.04	0.01	0.04	-0.28	-0.08	-0.12	-0.02	-0.12	-0.10	-0.02	-0.03	0.08	-0.17	-0.14	-0.03	1.00	
<i>FacultySize (17)</i>	0.04	0.00	0.02	-0.02	-0.06	-0.06	0.00	0.08	0.05	0.04	-0.04	0.09	0.01	0.07	-0.08	-0.15	1.00

ONLINE APPENDIX

Online Appendix Table 1. Baseline Estimates under matching scheme 1 (specify as control scientists those that belong to academic units that are similar to the academic unit of the rotator). The dependent variable is the sum of funds raised from the NSF.

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
<i>Ex-Post</i>	66,903.37*** (15,896.00)	68,131.90** (33,787.21)	62,511.36*** (16,328.62)	61,087.52*** (17,079.95)	57,172.13 (34,243.00)
<i>Rotator Group</i>	872.21 (25,566.59)	-9,120.31 (60,733.98)	2,252.63 (26,710.92)	318.87 (28,558.77)	-12,082.80 (60,414.40)
<i>Ex-Post * Rotator Group</i>	116,371.91*** (35,540.53)	-64,048.21 (83,396.32)	80,986.72** (37,206.31)	148,253.26*** (39,848.61)	-68,838.80 (83,028.55)
<i>Tenure</i>		-723.95 (1,186.83)			-787.43 (1,178.27)
<i>Ex-Post * Tenure</i>		-33.08 (1,511.62)			-54.99 (1,500.92)
<i>Tenure * Rotator Group</i>		463.02 (3,094.59)			574.26 (3,163.53)
<i>Tenure * Ex-Post * Rotator Group</i>		10,307.69** (4,242.00)			11,318.76*** (4,357.17)
<i>Knowledge Similarity</i>			887.41 (9,091.03)		743.27 (9,063.92)
<i>Knowledge Similarity * Ex-Post</i>			14,356.08 (12,814.02)		15,015.22 (12,780.10)
<i>Knowledge Similarity * Rotator Group</i>			-5,688.87 (40,960.17)		-2,257.24 (41,013.18)
<i>Knowledge Similarity * Ex-Post * Rotator Group</i>			237,755.64*** (65,380.30)		212,590.85*** (65,486.57)
<i>Productivity Similarity</i>				-8.85 (36.99)	-8.14 (36.64)
<i>Productivity Similarity * Ex-Post</i>				46.60 (54.04)	53.42 (53.51)
<i>Productivity Similarity * Rotator Group</i>				-0.23 (203.29)	18.17 (207.29)
<i>Productivity Similarity * Ex-Post * Rotator Group</i>				474.98 (-283.81)	670.17** (-290.41)
<i>OtherFunds</i>	-6,548.64 (20,157.63)	-3,640.01 (20,118.34)	-3,936.25 (19,995.16)	-7,712.97 (20,188.89)	-2,488.03 (19,968.97)
<i>NSFBefore</i>	32,635.12** (15,239.22)	29,929.99 (15,339.60)	28,615.30 (15,279.11)	32,555.16** (15,262.54)	25,868.77 (15,408.01)
<i>Years</i>	-1,913.08** (934.42)	-1,908.55** (931.24)	-18,36.83** (927.29)	-1,765.46 (938.51)	-1,643.58 (927.53)
<i>Position</i>	25,783.64** (12,512.40)	25,820.46** (12,523.71)	25,830.12** (12,407.08)	25,667.01** (12,512.54)	25,816.69** (12,408.58)
<i>Administrator</i>	-25,967.63 (14,981.42)	-24,322.19 (14,953.74)	-25,867.30 (14,865.75)	-28,514.95 (15,032.60)	-27,583.81 (14,865.70)
<i>Male</i>	-7,562.89 (20,586.50)	-5,421.26 (20,543.16)	-7,685.60 (20,410.36)	-10,489.03 (20,664.00)	-9,276.94 (20,412.67)
<i>Publications</i>	169.90 (294.58)	139.32 (293.87)	196.91 (292.34)	195.66 (327.60)	200.53 (323.71)
<i>Citations</i>	-97.67 (251.15)	-87.49 (250.77)	-76.25 (249.14)	-82.42 (255.43)	-53.84 (252.63)
<i>CoAuthors</i>	8,117.02 (6,195.30)	7,593.75 (6,189.77)	7,039.99 (6,153.06)	8,259.50 (6,210.16)	6,793.49 (6,157.49)
<i>UniversityQuartile</i>	-5,119.50 (8,210.83)	-2,043.80 (8,369.46)	-3069.64 (8,177.81)	-4,964.31 (8,213.67)	430.20 (8,342.38)
<i>FacultySize</i>	110.55 (433.25)	327.84 (441.94)	242.46 (432.17)	89.77 (434.18)	448.35 (440.50)
<i>Constant</i>	-75,500.04 (74,474.98)	-74,202.74 (77,191.03)	-84,750.94 (73,937.16)	7,252.23 (64,522.89)	-83,545.93 (76,609.56)
Year fixed effects included	YES	YES	YES	YES	YES
Science field fixed effects included	YES	YES	YES	YES	YES
Observations	1,302	1,302	1,302	1,302	1,302
Adjusted R ²	0.055	0.062	0.063	0.056	0.075
F-test for overall model significance	3.92	3.85	3.93	3.59	3.77

Standard errors in parentheses

*** p<0.01, ** p<0.05

Online Appendix Table 2. Baseline Estimates under matching scheme 2 (specify as control scientists those that are similar to scientists in the rotator academic unit). The dependent variable is the sum of funds raised from the NSF.

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
<i>Ex-Post</i>	64,423.86*** (15,719.94)	46,318.41 (33,761.21)	62,601.85*** (16,133.44)	64,028.47*** (16,907.79)	43,047.83 (34,570.83)
<i>Rotator Group</i>	-2,232.34 (24,850.99)	-18,164.89 (59,381.64)	-1,672.11 (25,905.09)	1,536.27 (27,735.94)	-15,962.34 (59,342.75)
<i>Ex-Post * Rotator Group</i>	110,009.45*** (34,503.76)	2,020.15 (81,493.88)	74,117.07 (35,964.03)	130,638.15*** (38,449.82)	-17,554.99 (81,539.63)
<i>Tenure</i>		-1,029.19 (1,210.70)			-1,108.47 (1,200.57)
<i>Ex-Post * Tenure</i>		985.54 (1,596.34)			1,013.55 (1,583.25)
<i>Tenure * Rotator Group</i>		863.13 (2,919.81)			961.57 (2,957.03)
<i>Tenure * Ex-Post * Rotator Group</i>		5,861.48 (3,984.77)			6,553.88 (4,038.90)
<i>Knowledge Similarity</i>			-86.28 (9,696.00)		24.20 (9,691.07)
<i>Knowledge Similarity * Ex-Post</i>			6,889.98 (13,566.73)		6,986.35 (13,563.74)
<i>Knowledge Similarity * Rotator Group</i>			-5,876.36 (40,983.55)		-5,954.42 (41,007.94)
<i>Knowledge Similarity * Ex-Post * Rotator Group</i>			252,240.97*** (65,302.98)		244,345.56*** (65,289.60)
<i>Productivity Similarity</i>				14.09 (45.83)	14.41 (45.83)
<i>Productivity Similarity * Ex-Post</i>				-2.05 (62.03)	(45.45) 1.55
<i>Productivity Similarity * Rotator Group</i>				-51.33 (214.59)	(61.54) -42.45
<i>Productivity Similarity * Ex-Post * Rotator Group</i>				385.33 (-297.04)	(-217.45) 517.36
<i>OtherFunds</i>	-3,419.38 (21,044.01)	-1,473.15 (21,046.49)	-96.87 (20,907.21)	-5,129.57 (21,083.12)	-50.51 (20,937.23)
<i>NSFBefore</i>	37,289.90** (15,242.68)	37,784.58** (15,251.27)	31,341.13** (15,241.86)	36,119.08** (15,264.02)	30,652.36** (15,262.53)
<i>Years</i>	-1,866.75** (950.98)	-1,896.96** (950.17)	-1,763.36 (944.14)	-1,662.50 (960.28)	-1,548.59 (951.88)
<i>Position</i>	19,202.96 (12,466.49)	19,551.12 (12,547.85)	19,354.14 (12,369.12)	18,309.93 (12,585.47)	18,706.60 (12,558.47)
<i>Administrator</i>	-15,681.36 (15,040.93)	-14,415.65 (15,055.10)	-15,705.62 (14,946.79)	-17,122.03 (15,192.78)	-16,215.29 (15,086.89)
<i>Male</i>	-7,470.98 (22,656.08)	-5,856.27 (22,648.74)	-7,354.58 (22,475.48)	-10,180.81 (22,723.46)	-8,894.45 (22,512.60)
<i>Publications</i>	256.87 (384.81)	229.14 (384.90)	283.83 (381.85)	386.71 (394.50)	414.63 (391.09)
<i>Citations</i>	49.16 (241.09)	67.32 (241.10)	76.66 (239.36)	39.24 (242.17)	82.70 (240.33)
<i>CoAuthors</i>	8,585.06 (5,944.01)	7,951.59 (5,946.11)	8,033.51 (5,904.91)	9,250.67 (5,953.16)	8,181.40 (5,910.16)
<i>UniversityQuartile</i>	-2,778.58 (8,207.32)	-267.32 (8,418.42)	-1,457.51 (8,164.50)	-2,978.09 (8,219.69)	1,062.84 (8,380.33)
<i>FacultySize</i>	22.61 (380.73)	44.85 (384.05)	158.61 (380.39)	27.32 (388.71)	184.00 (391.87)
<i>Constant</i>	-56,043.60 (109,981.61)	-63,357.80 (80,104.62)	-78,315.59 (78,049.34)	-68,884.65 (78,695.99)	-54,131.88 (110,442.51)
Year fixed effects included	YES	YES	YES	YES	YES
Science field fixed effects included	YES	YES	YES	YES	YES
Observations	1,322	1,322	1,322	1,322	1,322
Adjusted R ²	0.053	0.055	0.090	0.053	0.064
F-test for overall model significance	3.82	3.55	4.22	3.45	3.39

Standard errors in parentheses

*** p<0.01, ** p<0.05

Online Appendix Table 3. Baseline Estimates under matching scheme 4 (specify as control scientists those that are in the rotator's university but in a different, still comparable, academic unit). The dependent variable is the sum of funds raised from the NSF.

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
<i>Ex-Post</i>	45,702.68** (21,864.95)	36,963.45 (41,471.60)	44,268.77** (22,093.24)	40,057.25 (23,321.29)	26,204.42 (42,257.53)
<i>Rotator Group</i>	-3,772.78 (26,455.70)	-22,539.18 (61,263.17)	-4,675.71 (27,132.63)	-7,098.15 (29,306.99)	-30,940.08 (60,713.22)
<i>Ex-Post * Rotator Group</i>	93,309.93** (36,782.89)	-88,129.95 (82,805.13)	51,788.98 (37,732.49)	116,498.46*** (40,894.15)	-102,456.78 (82,244.95)
<i>Tenure</i>		-506.01 (1,542.25)			-590.25 (1,517.60)
<i>Ex-Post * Tenure</i>		524.96 (2,048.94)			677.38 (2,010.59)
<i>Tenure * Rotator Group</i>		973.35 (2,987.19)			1,132.50 (2,962.22)
<i>Tenure * Ex-Post * Rotator Group</i>		9,605.02** (4,037.80)			9,895.74** (4,002.02)
<i>Knowledge Similarity</i>			1,118.31 (9,003.91)		-70.12 (9,011.70)
<i>Knowledge Similarity * Ex-Post</i>			4,525.50 (12,035.43)		5,858.59 (12,013.98)
<i>Knowledge Similarity * Rotator Group</i>			1,577.10 (38,333.47)		2,664.23 (38,070.06)
<i>Knowledge Similarity * Ex-Post * Rotator Group</i>			283,544.52*** (60,825.65)		272,777.10*** (60,357.41)
<i>Productivity Similarity</i>				-43.74 (44.91)	-41.28 (43.60)
<i>Productivity Similarity * Ex-Post</i>				38.32 (57.22)	40.11 (55.54)
<i>Productivity Similarity * Rotator Group</i>				-25.18 (195.61)	-7.82 (192.51)
<i>Productivity Similarity * Ex-Post * Rotator Group</i>				303.11 (-269.37)	430.19 (-265.47)
<i>OtherFunds</i>	-1,729.69 (26,088.10)	5,663.71 (25,972.80)	6,096.85 (25,676.99)	-3,202.71 (26,156.49)	11,374.12 (25,575.15)
<i>NSFBefore</i>	28,091.16 (19,608.59)	25,951.46 (19,631.61)	14,098.37 (19,471.69)	27,996.46 (19,632.19)	11,858.76 (19,534.01)
<i>Years</i>	-188.35 (1,202.60)	-115.66 (1,192.84)	-31.95 (1,178.79)	-1.33 (1,210.99)	278.62 (1,176.62)
<i>Position</i>	22,227.37 (16,775.48)	19,083.79 (16,860.58)	24,010.99 (16,491.12)	24,059.92 (16,834.16)	22,452.17 (16,569.52)
<i>Administrator</i>	-14,227.21 (19,209.26)	-12,974.60 (19,061.27)	-12,852.24 (18,781.03)	-18,492.13 (19,374.60)	-16,667.71 (18,771.45)
<i>Male</i>	-14,252.50 (28,265.60)	-13,646.86 (28,033.42)	-13,926.03 (27,654.48)	-18,971.79 (28,440.11)	-18,814.30 (27,558.37)
<i>Publications</i>	352.56 (248.94)	383.51 (250.16)	366.47 (244.23)	490.09 (292.78)	537.10 (287.75)
<i>Citations</i>	-28.02 (437.52)	20.02 (434.14)	27.41 (427.80)	73.45 (452.17)	164.78 (438.13)
<i>CoAuthors</i>	9,883.19 (7,911.92)	9,679.21 (7,852.41)	8,449.50 (7,817.50)	10,483.71 (7,931.51)	9,244.23 (7,764.42)
<i>UniversityQuartile</i>	-2,811.70 (10,055.75)	4,667.60 (10,776.69)	1,507.77 (10,207.42)	-3,771.88 (10,078.59)	8,057.41 (11,005.29)
<i>FacultySize</i>	-150.78 (361.34)	-213.63 (359.79)	27.72 (359.04)	-179.73 (362.38)	-77.04 (358.10)
<i>Constant</i>	-40,852.19 (68,791.20)	-17,340.60 (73,052.43)	-29,715.19 (95,322.51)	-39,140.07 (69,005.50)	-148,218.38 (93,046.20)
Year fixed effects included	YES	YES	YES	YES	YES
Science field fixed effects included	YES	YES	YES	YES	YES
Observations	740	740	740	740	740
Adjusted R ²	0.053	0.068	0.096	0.052	0.160
F-test for overall model significance	2.64	2.87	3.70	2.41	3.53

Standard errors in parentheses

*** p<0.01, ** p<0.05

Evidence linked to managerial implications and the generalizability of our work (section Analysis and results)

Online Appendix Table 4. Split the sample according to the duration of the secondment.

VARIABLES	Secondment shorter than 16 months	Secondment longer than 16 months
<i>Ex-Post</i>	53,427.90*** (16,787.93)	62,428.18 (46,016.14)
<i>Rotator Group</i>	4,675.52 (24,664.59)	-6,728.32 (62,399.88)
<i>Ex-Post * Rotator Group</i>	17,825.47 (34,733.76)	244,980.64*** (88,012.20)
<i>OtherFunds</i>	3,618.68 (20,679.69)	-30,364.25 (57,336.46)
<i>NSFBefore</i>	23,264.45 (15,691.73)	78,450.67 (41,692.25)
<i>Years</i>	-798.89 (899.89)	-2,724.43 (2,625.73)
<i>Position</i>	-12,769.57 (16,069.86)	29,620.30 (42,756.25)
<i>Administrator</i>	-13,987.62 (15,153.61)	-27,521.63 (40,940.99)
<i>Male</i>	18,850.83 (21,256.22)	44,190.67 (78,559.68)
<i>Publications</i>	870.47 (460.51)	387.63 (1,126.94)
<i>Citations</i>	-71.64 (249.37)	-438.26 (1,282.04)
<i>Coauthors</i>	1,963.66 (5,430.85)	24,284.13 (18,859.79)
<i>UniversityQuartile</i>	-16,018.86** (7,952.54)	-7,347.90 (21,426.90)
<i>FacultySize</i>	124.25 (452.03)	453.27 (1,143.48)
<i>Constant</i>	46,706.38 (52,030.24)	-102,372.88 (144,320.93)
Year fixed effects included	YES	YES
Science field fixed effects included	YES	YES
Observations	454	408
Adjusted R ²	0.045	0.051
F	2.54	2.55

Standard errors in parentheses

*** p<0.01, ** p<0.05

Online Appendix Table 5. Limit the analysis to field-specific characteristics.

	Fields with by highest rejection rate	Most multidisciplinary fields	Fields with the highest technological turnover speed
<i>Ex-Post</i>	57,249.75** (26,321.50)	60,913.64 (49,883.69)	75,531.87 (47,477.73)
<i>Rotator Group</i>	-345.86 (39,664.63)	11,778.92 (67,534.22)	-800.09 (64,872.96)
<i>Ex-Post * Rotator Group</i>	112,752.99** (55,370.79)	195,906.96** (94,828.94)	227,943.70** (90,411.77)
<i>Constant</i>	-4,937.81 (128,676.42)	-176,252.14 (142,690.24)	-79,901.40 (181,221.75)
Controls included	YES	YES	YES
Year fixed effects included	YES	YES	YES
Science field fixed effects included	YES	YES	YES
Observations	531	288	355
Adjusted R ²	0.029	0.043	0.045
F	1.84	1.92	1.84

Standard errors in parentheses

*** p<0.01, ** p<0.05

We identified Engineering, Biology and Social Sciences as the fields with the highest rejection rates based on NSF (2015) <https://www.nsf.gov/nsb/publications/2015/nsb201514.pdf>

We identified Physics, Geology and Computer Sciences as the fields with the highest multidisciplinary based on Rinia et al. (2002) <https://link.springer.com/content/pdf/10.1023%2FA%3A1016078331752.pdf>

We identified Computer Sciences and Engineering as the fields that evolve faster based on Agrawal et al. (2017)

Evidence referring to testing the mechanism of political influence (section “Testing the mechanism and examining alternative explanations”)

To see if our baseline estimates reflect knowledge transfer rather than influence or bias, we leverage the fact that a few rotators moved to a new academic institution after their tenure at NSF. For those cases, the *ex-ante* and the *ex-post* colleagues are different. As such, under the premise that rotators act as conduits of knowledge transfer, any improvements in funding should occur only to the *ex-post* colleagues. Indeed, we compare the funding records of the rotator’s new and old colleagues. Given the small sample size and the fact that the *ex-ante* and *ex-post* academic units are not necessarily comparable, we present just descriptive statistics. As seen in Online Appendix Table 6, the new colleagues nearly doubled their average NSF funding from around \$55,000 before having a rotator colleague to about \$102,000 after. However, the average NSF funding records of the rotator’s former academic colleagues remained unchanged, from \$108,500 to \$107,502. In other words, if rotators are using their NSF connections to help their colleagues, they are not helping the colleagues they worked with before they went to NSF.¹

Online Appendix Table 6. Comparing *ex-ante* and *ex-post* NSF funding for new and old colleagues of rotators who after rotation changed employment.

Variable	Colleagues in original academic institution		Colleagues in new academic institution	
Average NSF funding <i>ex-ante</i>	\$	108,500	\$	54,577
Average NSF funding <i>ex-post</i>	\$	107,502	\$	101,747
Number of academics		443		952

Evidence referring to testing the mechanism of gains from other colleagues, co-authors or co-investigators (section “Testing the mechanism and examining alternative explanations”)

- a. Increased funding records may not reflect learning from the rotator but learning from other faculty members with success in raising funds from the agency. Because the academics we study did not raise NSF funds in the *ex-ante* period, it is hard to imagine that such learning occur previously. Accordingly, the main route such learning could materialize is if those with existing records gained additional NSF knowledge from the rotator, which then, in turn, they transmitted to colleagues with non-existing funding records. To test whether colleagues with existing records gained from the presence of rotators, we conduct the baseline analysis including in the sample only faculty members with one or more NSF grants in the *ex-ante* period.² The results, presented

¹ We interpret these results with caution as we cannot rule out the case that this handful of rotators changed employment because they did not have strong ties with their former colleagues in the first place or otherwise are different from the other rotators.

² Similarly, improvements in the funding record of those academics without NSF funding *ex-ante*, may also be initiated by the rotator but the full effect is completed once the new recipients of knowledge share their new knowledge with each other. If that holds, the empirical estimates would be attributed to the rotator only partially. In unreported exercises we conducted we did not find support for such mechanism.

as test 1 in Online Appendix Table 7 (which for ease of exposition reports only the variables that test the hypotheses) do not show improvements for those academics, as the *Ex-Post * Rotator Group* interaction is not statistically significant (The inflated size of the coefficients is due to 9 scientists who pulled the regression line upwards as their *ex-ante* accumulation of NSF grants was in the order of 10 million and above.) Hence, it is unlikely that learning from colleagues with existing funding records, present in the same academic unit both in the *ex-ante* and in the *ex-post* period, is driving our findings.

- b. Our results might be driven by the co-authors or the co-investigators of the rotator colleagues, not the rotator. To test this we omit from the analysis scientists whose more recent frequent co-authors or co-investigators experienced significant improvement in their *ex-post* NSF funding record. Specifically, we omit from the analysis academics whose at least 1 of the 10 most frequent *ex-post* co-authors or co-investigators raised more than \$200,000 from the NSF *ex-post* while their *ex-ante* NSF grant accumulation was below \$10,000. The results from this test, presented in Online Appendix Table 7 as test 2 and 3 respectively, are similar to the baseline estimates. As such, these results suggest that the NSF funding increases we reveal are not driven by learning from co-authors or co-investigators.³

Online Appendix Table 7. Testing alternative possible mechanisms.

	Test 1 - Include in the sample only colleagues with NSF grants <i>ex-ante</i>		Test 2 - Omit from the sample rotator colleagues whose co-authors raised grants from the NSF recently		Test 3 - Omit from the sample rotator colleagues whose Co-Investigators raised grants from the NSF recently	
	Specification without moderators	Specification with moderators	Specification without moderators	Specification with moderators	Specification without moderators	Specification with moderators
<i>Ex-Post * Rotator Group</i>	803,339.52 (568,323.44)	541,029.73 (926,502.34)	112,107.48** (48,806.95)	-75,767.78 (128,751.72)	126,356.20*** (46,295.84)	-29,953.28 (112,560.82)
<i>Tenure * Ex-Post * Rotator Group</i>		-27,562.35 (43,114.01)		12,852.64** (6,798.28)		13,878.78** (5,990.363)
<i>Knowledge Similarity * Ex-Post * Rotator Group</i>		1,034,679.23 (588,026.63)		297,046.56** (92,428.66)		106,147.42 (86,055.48)
<i>Productivity Similarity * Ex-Post * Rotator Group</i>		998.03 (-6,116.29)		1,033.40 (-672.55)		1,191.93** (-521.81)
Level terms and two-way interactions	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects included	Yes	Yes	Yes	Yes	Yes	Yes
Science field fixed effects included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	627	627	725	725	834	834
F-test	2.04***	5.21***	2.05***	2.57***	2.27***	1.85***
Adj. R ²	0.041	0.051	0.049	0.076	0.038	0.039

Standard errors in parentheses

*** p<0.01, ** p<0.05

³ The potential influence of the co-investigators is zero for the large majority of the sample grants as 80 percent of them do not have a co-investigator. Moreover, we do not find statistically significant differences in the funding levels when breaking down the grants by the number of co-investigators except for 5 grants with 8 co-investigators.

Evidence referring to testing whether an increase in the average size of grants is driving the results (section “Testing the mechanism and examining alternative explanations”)

Online Appendix Table 8. Comparison between the average grant size for the population and sample.

Directorate	Average grant size (population)	Average grant size (sample)
Directorate for Biological Sciences	\$ 343,099	\$ 335,622
Directorate for Education & Human Resources	\$ 491,759	\$ 997,248
Directorate For Engineering	\$ 275,473	\$ 288,537
Directorate for Geosciences	\$ 1,010,212	\$ 293,788
Directorate for Mathematical & Physical Sciences	\$ 447,239	\$ 508,786
Directorate for Social, Behavioral & Economic Sciences	\$ 196,899	\$ 159,309
Directorate for Computer & Information Science & Engineering	\$ 421,860	\$ 491,000
Office Of The Director	\$ 196,082	\$ 492,060
Total	\$ 414,221	\$ 393,742

Evidence referring to footnote 15

A plausible concern is that perhaps only the more productive scientists maintain updated online CVs, LinkedIn pages, and the like. Ge et al. (2016) provide evidence that online sources can be used for building reliable career histories for all academics. Still, if the concern is valid, our sample could be biased by excluding less productive academics. The fact that we use multiple data sources to collect information along with the varying publication, citation, and funding records of the sample academics alleviates such concern. To illustrate, as shown in Table 1, the standard deviation of the publications and citations variables is on par and surpasses their mean respectively and this indicates the wide distribution of the values for these variables. Moreover, given that for the sample academics the vast majority of grants are first-time grants we compare these grants to the total population of NSF grants from 1990 onwards. The average inflation adjusted amount of the 932 first time grants in our database is \$393,741. The corresponding figure for the 107,916 first time grants that NSF has awarded across directorates since 1990 is \$414,221. The difference between the two figures is not statistically significant. As such, the evidence suggests that the grants in the sample, and likely the sample scientists that attracted them, are representative of the population.

References

- Agrawal, A., A. Galasso, A. Oettl. 2017. Roads and Innovation. *The Review of Economics and Statistics* **99**(3) 417-434.
- Ge, C., K.W. Huang, I.P. Png. 2016. Engineer/scientist careers: Patents, online profiles, and misclassification bias. *Strategic Management Journal* **37**(1) 232-253.
- NSF. 2015. Report to the National Science Board on the National Science Foundation's Merit Review Process Fiscal Year 2014.
- Rinia, E., T. van Leeuwen, E. Bruins, H. van Vuren, A. van Raan. 2002. Measuring knowledge transfer between fields of science. *Scientometrics* **54**(3) 347-362.