The Journal of Technology Transfer (2020) 45:276–303
https://doi.org/10.1007/s10961-018-9681-5

"Another roof, another proof": the impact of mobility on individual productivity in science

Valentina Tartari[1] · **Francesco Di Lorenzo**[2] · **Benjamin A. Campbell**[3]

Published online: 13 July 2018

Abstract
The mobility of highly skilled employees is seen as a critical way for organizations to transfer knowledge and to improve organizational performance. Yet, the relationship between mobility and individual performance is still largely a theoretical and empirical puzzle. Integrating human capital mobility research and the economics of science literature, we argue that mobility of academics should have a positive effect on individual productivity. Additionally, we argue that this positive effect is strengthened when academics move towards better-endowed institutions. We find support for our predictions using a unique dataset of 348 academics working in biology department in the United Kingdom supplemented with qualitative evidence from a survey of the focal academic researchers.

Keywords Mobility · Academic researchers · Scientific productivity · Organizational resources · Arellano–Bond

JEL Classification J24 · J62

"Another roof, another proof" (Paul Erdős).
Quoted in A Tribute to Paul Erdős (1990) edited by Alan Baker, Béla Bollobás, A. Hajnal, Preface, p. ix.

1 Introduction

Paul Erdős is the most prolific author in the history of mathematics. "In a never-ending search for good mathematical problems and fresh mathematical talent, Erdős crisscrossed four continents at a frenzied pace, moving from one university or research center to the next. His modus operandi was to show up on the doorstep of a fellow mathematician, declare, "My brain is open," work with his host for a day or two, until he was bored or his host was run down, and then move on to another home" (Hoffman 1999, p. 6). Erdős wrote

✉ Valentina Tartari
vt.ino@cbs.dk

1 Department of Strategy and Innovation, Copenhagen Business School, Frederiksberg, Denmark

2 Department of Strategy and Innovation, Copenhagen Business School, Frederiksberg, Denmark

3 Fisher College of Business, The Ohio State University, Columbus, USA

1475 substantial academics papers with over 500 different co-authors located all over the world, and even in the late years of his life he published over 50 papers a year, more than a good mathematician would publish in a lifetime.

Stories like Erdős’ reinforce the popular perception that knowledge workers are able to take their talent with them wherever they go, like athletes whose ability can be purchased by the highest paying team. Accordingly, employee mobility affects the performance of both the source and recipient organizations (Aime et al. 2010; Campbell et al. 2012a; Corredoira and Rosenkopf 2010; Rosenkopf and Almeida 2003; Somaya et al. 2008). From the point of view of organizations, understanding whether hiring highly-skilled workers from external organizations is ultimately a value-creating or value-destroying proposition is critical in building and maintaining a sustainable human capital-based competitive advantage (Campbell et al. 2012a; Campbell et al. 2012b; Carnahan et al. 2012; Coff 1997). Employee mobility also creates important opportunities and challenges for policy makers, as governments would like on the one hand to promote greater mobility of highly skilled individuals into positions that enhance value creation for society (i.e. through initiatives such as ERA in Europe), yet on the other hand fear the possibility of a “brain drain” of talented individuals from their own country. Further, employee mobility is facilitated by collaborative work (Campbell et al. 2018) which can in turn enhance innovation outcomes (Audretsch et al. 2002; Feldman et al. 2012). From the perspective of individuals, there is also a clear interest in understanding how their mobility patterns will affect their own personal performance, which will in turn affect their career prospects both inside their workplaces and in the external labor market.

The extant literature on the impact of individual mobility on individual performance is conflicted. First, it is not clear empirically whether individual productivity has a positive or negative effect on the likelihood of inter-organizational mobility (Campbell et al. 2012b; Di Lorenzo and Almeida 2017; Groysberg et al. 2008; Hoisl 2007). Second, it is not evident whether inter-organizational mobility increases or decreases the individual productivity of the moving employee (Fernandez-Zubieta et al. 2015; Hoisl 2007), which opens questions about the portability of the competitive advantage generated by talented human capital (Groysberg et al. 2008; Wezel et al. 2006). In particular, while we observe a strong policy focus on researchers’ mobility and scientific performance at the macro level, we currently lack systematic evidence on the effect of academics’ mobility on their individual scientific productivity (Fernandez-Zubieta et al. 2016), with studies indicating the possibility of both positive or negative effects of mobility on researchers’ publication output.

The lack of consistency in the results provided in previous studies indicates that mobility is a complex phenomenon with uncertain effects on individual performance (Mawdsley and Somaya 2016). This paper addresses the question of whether mobility affects individual scientific productivity through the lens of multiple interacting forces. Through this lens, we explore how organizational resources moderate the relationship between mobility and scientific productivity. We test our hypotheses on researchers in academia. In addition to helping answer a still open question in the economics of science literature regarding the dynamics of academic careers, we contribute to the more general literature on employee mobility.

This study also advances the methodology employed in previous research on mobility and individual performance. Recognizing the inherent issue of simultaneity in the mobility-performance relationship (Hoisl 2007; Singh and Agrawal 2011) and the dynamic nature of performance in this context, we implement an instrumental variable approach combined with an Arellano–Bond GMM estimator to estimate the focal relationships. Leveraging a unique dataset of 348 academics working in biology department in the United Kingdom, we show that mobility has a positive effect on individual productivity as predicted. We also find that this positive effect is strengthened when academics move towards better-endowed institutions.

2 Mobility and individual performance of academics

The extant literature on the effect of mobility on post-move individual performance provides mixed results. Focusing on inventors of European patents, Hoisl (2007) finds that movers are 14.5% more productive than non-movers and attributes this effect to better employee-employer matching and knowledge spillovers from new colleagues. In contrast, in a sample of star security analysts, Groysberg et al. (2008) find that individuals who switch employers experience an immediate decline in performance which persists for multiple years due to the disruptive effects of mobility on routines and social capital. This tension between the positive effects associated with matching and knowledge spillovers versus the negative effect associated with disruption of routines and social capital is pervasive in the literature on the impact of mobility on individual performance.

Focusing on mobility of academic researchers, recent contributions provide sophisticated econometric evidence on spill-over and peer effects resulting from academic mobility (Borjas and Doran 2012; Moser et al. 2014; Waldinger 2012), yet most evidence on the relationship between mobility and individual scientific productivity are mainly descriptive in nature, and yield contrasting results. In a study of researchers in one Spanish university, De Filippo and Casado (2009) find that mobile researchers are more productive and cited than other researchers. Aksnes et al. (2013), find a similar result, albeit weaker, analyzing a sample of 1100 Norwegian academics. In a more recent study using data from 16 different countries, Franzoni et al. (2014) find that academics who have spent time abroad publish papers with higher impact than their non-mobile colleagues. Using a sample of Dutch researchers in three disciplines (physics, chemistry and economics), van Heeringen and Dijkwel (1987) observe a fall in productivity shortly after a job change, followed by an increase few years later, but no effect on citations. Cañibano et al. (2008) show that international mobility does not improve publication performance, and Cruz-Castro and Sanz-Menéndez (2010) find no effect of postdoctoral mobility on publication output. A more recent contribution by Fernandez-Zubieta et al. (2016) finds that for British researchers in physical sciences, job mobility is weakly associated with a short-term decrease in performance, which is reversed only in the case academics move to more prestigious departments.

Extending on this existing literature, we argue that post-mobility performance is shaped by three different forces: positive treatment effects driven by knowledge spillovers and improved employee matching, negative treatment effects driven by disruption of routines and loss of firm- and relationship-specific human capital, and positive selection effects driven by worker autonomy when voluntarily choosing to move. In what follows, we examine the post-mobility performance of academic scientists through the lens of these three cumulative forces. In so doing, we note that the context of academic scientists is marked by low levels of asymmetric information on the job market as researchers have human capital that is highly transferable, they have great autonomy over with whom they work and on which projects they work, and they are members of durable communities that span organizational boundaries. Each of these characteristics has important implications for the cumulative effect of the interacting forces that shape post-mobility performance of academic scientists.

First, in general, it is difficult to objectively measure the performance of knowledge workers (Ernst and Vitt 2000). The high causal ambiguity between input and output in the value creation process means that, on average, the current employer is better than any other possible future employer in observing the value of the human capital embedded in each individual. This also means that the job market for highly-skilled individuals in knowledge-intensive industries is typically characterized by high asymmetric information (Chiang and Chiang 1990; Jovanovic 1979). When asymmetric information is high, the potential disruption effects of moving are greater because the quality of new employer-employee matches is worse on average than when asymmetric information is low.

The university context, however, is marked by easy-to-observe knowledge production outcomes. While publications are not perfect carriers of information (Lissoni et al. 2013), they are undoubtedly the main measure of individual performance in academia (Stephan 1996) and largely determine academics' career paths. In this context, asymmetric information is low and both employees and employers can effectively forecast post-mobility performance. As a consequence, academics will only move if they forecast that they will have higher performance which pushes expected post-mobility performance in the positive direction.

Second, organizations can reduce transferability of their employees' human capital through the development of firm-specific human capital and other labor market frictions (Campbell et al. 2017; Mahoney and Qian 2013). The presence of non-transferrable human capital has important implications for the relationship between mobility and individual performance. If the skills acquired while employed with a specific organization are not easily transportable or applicable to a new organization, then individuals will be less likely to move and/or will suffer a performance decline when they move to new employer due to a greater disruption in their firm-specific and co-specialized human capital (Groysberg et al. 2008). However, academic scientists have a portfolio of human capital with limited organization-specific components. This suggests that academic scientists experience minimal negative disruptive treatment effects when moving. Additionally, without a substantial organization-specific component, the set of alternate employers where the scientist could be more productive is potentially large, which again pushes expected post-mobility performance in the positive direction.

Third, a defining characteristic of academic research is that individual scientists value creative control and autonomy (Aghion et al. 2008; Stern 2004) and they retain decision rights over the projects they oversee and the methods used to tackle them. They are therefore an excellent example of knowledge workers as described by Drucker (1998, p. xi), owning their own means of production as "they carry the knowledge in their heads and can therefore take it with them". Given this level of autonomy and the freedom to work on projects and to choose their own team, the voluntary nature of mobility is enhanced for this context adding to the positive forces on post-mobility performance.

Finally, when trying to understand the impact of mobility on individual performance it is important to keep in mind that individuals often belong to social and professional communities external to the firm that give them access to resources based on the durable collaborations embodied in the community (Almeida et al. 2011). Recent research on the role of collaborations networks for knowledge workers suggests that these communities optimize the employer-employee match due to more available information on job opportunities for individuals and less asymmetries the firm on the quality of potential new hires human capital (Nakajima et al. 2010). Most importantly, employees using collaboration networks to change employers experience a significant increase in individual performance post-mobility. In the case of academia, the relational capital scientists have built in a previous employment period can be transported to the new employer, as all individuals still belong to the same community; therefore, mobility to a new employer implies a net increase in relational capital, which in turns improves productivity (Dokko and Rosenkopf 2009; Somaya et al. 2008). Moreover, researchers are embedded in so-called "invisible colleges" (Crane 1972), a term designating informal collectives of closely interacting scientists, and which are significant social and cognitive formations that advance the research fronts of science (De Solla Price 1986). As such, university researchers are not prevented from collaborating across universities and may belong to multiple organizational communities simultaneously while developing their research activities. This implies that the positive treatment effects from knowledge spillover are relatively larger than the negative disruptive effects since academic scientists do not necessarily lose any prior connections but they do gain new connections when changing employers. Additionally, since academic scientists do not lose prior connections, the opportunity costs of changing employers is relatively low which thus enhances the positive effect on post-mobility performance.

Considering that the academic profession is characterized by easy portability of human capital, low asymmetric information on human capital quality, and persistent social networks, the disruptive effects of mobility highlighted by Groysberg et al. (2008) are likely minimal, which facilitates the positive effects driven by matching and knowledge spillover mechanisms highlighted by Hoisl (2007) and the positive effects associated with the voluntary nature of mobility to dominate. Thus, for this context, we hypothesize:

H1 Academics experience a gain in productivity after moving to a new university.

In order to better understand the relationship between employee mobility and individual performance, we also explore how organizational characteristics influence the highlighted focal forces that shape the performance of moving individuals. The resource-based theory of the firm suggests that organizations with superior resources tend to outperform competitors (Barney 1991; Peteraf 1993). Moreover, inside organizations, knowledge is embedded in individuals but combined in organizational routines (Kogut and Zander 1992), supporting the idea of the existence of a complementarities between human capital and organizational resources (Mackey et al. 2013). This implies that in the presence of the same endowment of human capital, superior resources in the organization matter in having an impact on the productivity of each individual employee accessing those resources, and ultimately on organizational performance.

In academic science, the importance of resources for individuals' productivity is undoubtedly of great importance. As already articulated by Price in one of his last public lectures, the production of scientific knowledge requires much more than putting on "some sort of new thinking cap," but requires also access to a considerable amount of resources in terms of both equipment and colleagues (de Solla Price 1986, p. 247). In particular, research in life sciences is especially labor-intensive and requires large investments to set up laboratories (Levin and Stephan 1997). This means that, ceteris paribus, researchers employed in better-endowed universities perform better than their colleagues employed in worse endowed universities. In other words, we expect the former to show a greater number of publications and citation rates (Hagstrom 1971). This association between productivity and departmental quality (or prestige) are shaped by the same forces focused on above. Traditionally (and consistently to the universalism norm in science), sociologists of science have assumed that this association was caused by selection, where better institutions are more successful at attracting (and retaining) the best faculty members (Merton 1973). This idea has also been recently discussed in theoretical and empirical research about mobility of talented employees in knowledge-intensive industries (Gambardella et al. 2010). An additional force driving this relationship is that there are treatment effects where better departments are able to improve the productivity of their members (Long 1978) thanks to superior facilities such as laboratories, equipment, and access to the best graduate students and post-docs (Hagstrom 1971). Indeed, Allison and Long (Allison and Long 1990) found that scientists moving to prestigious institutions (where prestige is highly correlated with organizational endowment) tend to increase their productivity. Furthermore, an environment characterized by a large amount of resources clearly signals the ability to attract funding, which in turn increases the performance of a department and also increases its chances of getting additional funding, through the mechanisms of cumulative advantage at work in science, known as Matthew's affect (Merton 1968). Thus,

H2 Academics moving to better-endowed departments experience a higher gain in productivity than academics moving to similarly or less-endowed departments.

3 Data

3.1 Academics in UK universities

We analyze our hypotheses in the context of bioscience academic researchers employed in the United Kingdom. In 2008, researchers in the UK published 76,683 scientific articles, the third highest performance in the OECD area after the United States and Japan (OECD 2010), making the country an elite performer in science. Universities in the UK are highly autonomous in terms of budget, recruitment, and choices of curricula. The funding regime of UK universities makes the academic system extremely competitive and entrepreneurial. The funding for science and research activities in universities provided by the central government follows three main routes. The first is the so-called Dual Support system, which is composed by a block grant funding for Higher Education Institutions, complemented by project funding. The block grant funding is administered by the Higher Education Funding Council for England (HEFCE) (and analogous bodies in Wales, Scotland and Northern Ireland). In order to determine the allocation of this part of funding, the HEFCE (and local equivalents) perform a periodic assessment of British universities part (the Research Assessment Exercise, now called Research Excellence Framework). The main aim of this funding is to provide resources for basic research infrastructure and permanent staff salaries. Its entity is however of limited (especially if compared with project funding) and permanent staff positions are mainly funded through the money the government distributes to higher education institutions for teaching activities (the HEFCE has distributed £1.4 billion to support learning and teaching in universities and colleges for the academic year 2016–2017).

The project funding comes from specific programs of the seven Research Councils through grants to individual academics and departments: proposals are evaluated by peer review and the allocation decision follows a strategic direction. In 2010, HEFCE distributed £1.73 billion as block grant funding, while the Research Councils awarded grants for £2.6 billion (HEFCE 2011). It is important to note that Principal Investigators funded by

Research Council are allowed to move their grants with them in case they change institution. Other public organizations (such as the NHS), foundations and firms also provide funds to British universities. For example, in 1998 the Wellcome Trust has established a partnership with the UK government to fund world-class biomedical research in the country. Unlike other academic systems in Europe, researchers are often required to acquire external resources through competition.

The second route is dedicated capital funding through the Science Research Investment Fund. The third route is the Knowledge Transfer funding, currently distributed by the Higher Education Innovation Fund (HEIF). Funding includes support for a range of commercial activities, including academics' commercial ventures, personnel exchanges between university and industry, and university patenting; however, the majority of these funds have been used to build up and extend the efforts of university TTOs (Mustar and Wright 2009).

Two more issues are particularly interesting in the British context. First, the absence of a tenure-track system: once hired in a faculty position, individuals have a three-year probation period, after which the contract is made permanent (conditional on a positive assessment). Second, academic salaries are generally comparable across institutions as they vary within a well-defined national range (based on experience), with more flexibility only at the top of the career ladder (i.e., full professorship positions) (Deloitte 2012).

3.2 Sample construction

The study is based on a sample of 348 active research academics working in life science departments of British universities from 1995 to 2009. In order to avoid selection bias we have tried to construct a representative sample based on a cohort approach. This is very important as we want to analyze individuals across the whole spectrum of productivity, and not only star performers (Groysberg et al. 2008) or researchers obtaining prestigious grants (Fernandez-Zubieta et al. 2016). We first selected seven leading British universities (University of Cambridge, University of Oxford, University of Edinburgh, University College London, Imperial College London, University of Glasgow, and University of Birmingham), and extracted the surnames and initials of all faculty members included in the 2001 Research Assessment Exercise (RAE) in the Unit of Assessment (UoA) 14 (Biology): this gave us a list of 1026 researchers (for a breakdown by institution see Appendix 1). From this list we proceeded to manually look for the personal webpages of this researchers in order to collect their CVs (usually in the form of pdf or word document). When a researcher was found but the CV was not available, we contacted him or her directly via asking for the CV. Appendix 1 shows how many CVs we retrieved. We decided to compile our list of researchers from the RAE in 2001 so that we would have a long enough history for most researchers. This meant however that several researchers could not be found as they had changed career, retired, or passed away. We ended up with 409 retrieved CVs, which corresponds to 40% retrieval rate, in line with usual response rates in surveys directed to academics (Perkmann et al. 2013). Two reasons are behind our choice of a single discipline, namely biology. First of all, we wanted to make sure that output measures could be easily comparable across individuals. Second, biology researchers tend to publish in smaller teams than in other fields such as experimental physics or medicine (Wuchty et al. 2007) making the link between a specific individual and her scientific production less ambiguous.

We manually coded the information retrieved from the CVs in order to construct detailed profiles of the researchers in our sample. This procedure resulted in a panel dataset spanning from 1952 to 2014, and containing information on demographic characteristics, education, and employment history. CV data have started to be widely used in economics and management research as they provide reliable information and accurate timing of events (Cañibano and Bozeman 2009; Geuna et al. 2015; Slavova et al. 2015).

In order to prepare the dataset for the analysis, we further excluded some researchers from the sample. First, we excluded all researchers who had been employed both in academia and in industry. As our measure of individual performance is based on the number of articles published, we needed to ensure that all scientists in our sample would face with similar incentives to publish along their career. As commercial firms seek protection of their findings through secrecy and other intellectual property rights in an attempt to profit from the knowledge they produce (Cohen et al. 2000), they generally limit possibilities of publication for their employees. Second, we decided to focus researchers with a career spanning several countries, so that our final sample would face similar macro-level and labor market issues during their career. At the end of this procedure, we were left with 348 in the time span 1995 to 2009. Data on student enrollment, university and department income and research quality were obtained using the publicly available datasets of the Higher Education Statistics Agency.

3.3 Variables

Our dependent variable, Scientific Productivity (*Scient_Prod_0*[1]), is defined as the cumulated count of journal articles published by each individual up to each point of time.[2] Priority of discovery is one of the main goals of the scientific community (Merton 1957) as the reward is the recognition awarded for being first. Publications are undeniably essential in establishing priority (Stephan 1996) and thus it is common practice to measure scientific with bibliographic indicators. To collect publication data we downloaded all peer-reviewed publications[3] of the researchers in our sample from Scopus Elsevier, which is recognized in the literature as a reliable source to collect publication data (Archambault et al. 2009). We also checked manually the efficacy and reliability of our crawling code, in order to avoid biases caused for example by homonymy.

We finally collected 18,033 peer-reviewed publications from 1995 to 2009, and Fig. 1 shows the characteristics of the distribution of Scientific Productivity. As Lotka's law predicts (Lotka 1926), the distribution is right-skewed. Thus, we are confident that our sample does not present particular biases due to its construction. We also applied a natural-logarithm transformation and lagged it one and two years (respectively *Scient_Prod_1*

[1] The "*0*" represents the number of years of lag.

[2] As a robustness check we have specified our models with Scientific Productivity as the yearly number of scientific publications (non-cumulated). Our results do not change. We have opted for cumulated values of scientific publications because we believe they are less sensitive to stochastic yearly fluctuations.

[3] Scopus Elsevier is a bibliographic database containing abstracts and citations for academic journal articles. It covers nearly 22,000 titles from over 5000 publishers, of which 20,000 are peer-reviewed journals in the scientific, technical, medical, and social sciences (including arts and humanities) (Scopus Info 2013). Scopus Elsevier allows legal downloading of data for research purposes.

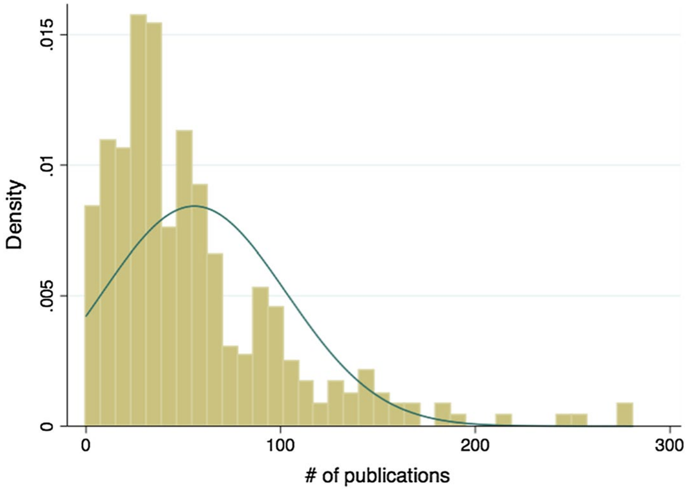

Fig. 1 Distributions of # of publication per academic

and *Scient_Prod_2*). In particular, we used Scientific Productivity lagged for one (*Scient_Prod_1*) year as a main dependent variable in our estimation models.[4]

Our independent variable is Mobility (*Mobility*) and it is directly extracted from the coded CV data. If an individual has never changed affiliation during her carrier, we coded each individual-year observation as 1. If an individual changed affiliation, we coded each individual-year observation with the second employer as 2. A similar logic is applied for any further change in the individual carrier in terms of affiliations. Hence, Mobility is the number of affiliations per each researcher tracked up to the period of observation.

Turning our attention to mobility, we observe that in general, the frequency of moves per researcher is skewed to the right. Almost 55% of the researchers (193) worked for only one employer in the timespan covered; 33% moved at least once (116 researchers); 10% worked for three employers (33 researchers); and less than 2% of them (6 researchers) worked for four employers.

To capture possible alternatives to Mobility as determinants of individual performance, we introduced a set of control variables in our models. First, Scientific Productivity, as a measure of individual performance, is likely to be explained by individual performance in a previous period. In highly knowledge-based contexts, performance is also a strong proxy for ability, which could explain both Scientific Productivity and Mobility; omitting this variable could potentially introduce strong biases in our performance models' estimates. Therefore, we controlled for Previous Productivity (*Prev_Prod*), which is the cumulated number of scientific publications per each individual up to the t-1 period.[5]

Second, scientific enquiry, especially in experimental disciplines, requires a large amount of resources, in terms of funds, laboratory equipment and human resources

[4] Using one and two years lag allowed us to model the time necessary for each moving researcher to produce and publish new scientific work. In particular, a one-year lag more realistically reflects the time between production and publication of a new academic article in academic bioscience research.

[5] In accordance with the lagged transformation of Scientific Productivity, we also generated three variables for *Previous Productivity*: Prev_Prod_0, Prev_Prod_1, and Prev_Prod_2.

(Stephan 1996). We therefore include in the regression the total amount of research grants available to each researcher in the sample in every year (*Ind_Grants*). To obtain this information, we manually matched each researcher in our sample in the database of awarded grants of the Biotechnology and Biological Sciences Research Council (BBSRC) since 1997,[6] which represents the major funding body in this scientific area. We also control for Department Research Funds (*Dept_Funds*), which is the amount of research funds available on average to each department employee. This information is collected through the records of the RAE in 2001 and 2008, and provides a complete overview (by year) of all funding received by each department. For this variable, the department is the one where our focal researcher is employed in each year. These two sources of funding research activities are independent and non-mutually exclusive in use.

To consider the level of research activity the department researchers are affiliated with, we also controlled for Ph.D. Students (*PhD_Stud*), which is the number of Ph.D. students active in the department where each focal researcher is affiliated every year. Finally, we include a control for Coauthors Affiliations (*Coa_Affil*), which is the average number of institutions where the focal researcher's coauthors are affiliated.

3.4 Identification strategy and estimation approach

The literature on the relationship between mobility and individual performance is characterized by several important empirical challenges. First, the simultaneous nature of this bi-directional relationship generates strong endogeneity issues. In a recent study, Singh and Agrawal (2011) observe that "mobility is endogenous, not random; firms make deliberate choices about who to recruit for a reason" (p. 147), inviting future researchers interested in the mobility-performance relationship to more systematically address this causality issue. In this sense, significant improvements have been proposed to model such endogeneity, such as using control-group design (Groysberg et al. 2008) and instrumental variable techniques (Hoisl 2007).

In addition to simultaneity, another source of endogeneity bias comes from the dynamic nature of individual performance over time, especially considering that performance is determined by previous performance levels, severely challenging the hypothesis of independence of the individual's performance from past realizations.

Our empirical analysis primarily aims at estimating the effect of academic mobility on individual productivity. Our empirical model is based on the following equation:

$$y_{it} = X_{it}\beta + \alpha_i + u_{it}$$

where y_{it} is the Scientific Productivity for each individual i in each period t, X_{it} is the mobility status (i.e., Mobility) for each individual i in each period t, β is the coefficient of X on y, α_i is the unobserved time-invariant individual effect for each individual i, and u_{it} the error term.

As mentioned earlier, this empirical model suffers from several sources of bias. First, we expect the relationship between productivity and inter-organizational mobility to be endogenous. There are two separate aspects that underlie such endogeneity. One aspect refers to the simultaneity inherent in this relationship; individual performance and individual

[6] The BBSRC was created in 1994, and it is currently the largest UK public funder of non-medical bioscience: in 2012, it disbursed £200 M for bio-scientific research.

inter-organizational mobility are indeed simultaneously determined (Hoisl 2007). The other aspect is an omitted-variable bias related to mobility. The fixed-effects (FE) method would allow us to model the part of variance of the scientific productivity explained by unobserved characteristics, both of the individual and the employer. However, there might also be unobservable factors at the level of the labor market for academics that affect both the opportunity and propensity to move of each individual and their individual performance.

To deal with this endogeneity issue, our identification strategy rests on the use of an instrumental variable (IV). Instrumental variable estimation is appropriate if it is possible to argue that some regressors determine the independent variable (Mobility, in our case) but not the dependent variable (Scientific Productivity, in our case). This strategy allows a consistent estimation of the performance equation, which is our main interest. We used the Students Enrolled (*Students*), which is the number of students enrolled at time t at the university where the researcher works in t + 1, as an instrumental variable.[7] As discussed previously, the government (through HEFCE) allocates universities funding for teaching-related activities based on the number of students enrolled. Among other uses (such as financing grants for students), this money is used to open permanent faculty positions. These openings affect the academic labor market, influencing, in turn, individual researchers' mobility. Thus, we expect a positive relationship between the Students Enrolled and Mobility.

Contrary to the relevance of the instrument, its exogeneity cannot be tested empirically. However, from a conceptual point of view, we offer the following reasons why we do not expect a direct effect of the number of students of the individual scientific performance. First, one can argue that students are extensively used in laboratories as research assistants, so a larger pool of students might imply more resource available to each professor to increase the research output. Yet, the number of students refers mainly to new enrollments in bachelor programs, which are more unlikely to be involved in laboratories when compared to late stage master students and Ph.Ds. Second, one can argue that an increase in the number of students implies an increase in teaching load, affecting ultimately research performance negatively. The contracts generated by the government's funds (through HEFCE) are either fully teaching-based or characterized by the expected teaching-research balance of any other position in the UK for the same job position. This means that when the student population increases and new courses are offered, new faculty members are hired to teach the new courses.[8] And this is also valid at the university level; in fact, while an increase in the number of students increases the resources a university can dispose of, these resources cannot be used to directly fund research projects. As highlighted previously, research in UK universities is mainly financed through the dual support system, and funds for teaching and research are administered and kept separately.

As an additional check towards the validity of our instrument, we check if the number of students is correlated to the quality of the research conducted in the university. We perform the test on all UK universities, correlating different measures of research productivity at the level of the university for the years 2001 and 2008 (average score in the RAE,

[7] For example, if researcher A works at University X in 2001 and moves to University Y in 2002, the instrument we would use is the number of students at University Y in 2001.

[8] In other words, an increase in the number of students enrolled does not entail an increase in teaching hours stated in the employment contract of each individual faculty member.

percentage of researchers classified as internationally excellent, rank) and the number of students. Pairwise correlations are close to zero.[9,10]

A second source of endogeneity refers to the inter-temporal dependence between the level of individual performance in every period and the level of performance in the previous period. Introducing the lagged individual performance level in the specification might raise issues of autocorrelation in our FE model (included in the instrumental variable identification) that would bias our results, implying the need for a dynamic panel-data (DPD) model as an additional identification strategy.

Therefore, taking into account the DPD nature of our data in addition to the presence of an omitted-variable bias, our final identification strategy is based on the approach of Arellano and Bond (1991). The Arellano–Bond approach is especially suited for our empirical setting as its estimator is designed for situations with: (a) “small T, large N” panels; (b) linear functional relationships; (c) a dependent variable which depends on its own past realizations; (d) no strictly exogenous independent variables; (e) fixed individual effects; (f) heteroskedasticity and autocorrelation within, but not across, individuals. The estimation process transforms regressors by first-differencing via the Generalized Method of Moments (GMM) (Hansen 1982). The main idea is to use first-differencing to eliminate individual effects and use all past information of the dependent variable as instruments.

4 Results

4.1 Main effect: mobility-productivity relationship

Table 1 shows descriptive statistics and correlation coefficients, Table 2 shows the coefficient estimates for the Fixed-Effects (FE) models and the Arellano–Bond (AB) model.

Table 2 has three models. Model 1 is an ordinary least square (OLS) including FE. In this specification, we did not model the simultaneity issue between *Scientific Productivity* and *Mobility*, but rather took into account the effect of the unobserved heterogeneity at the individual level characterizing our design. Looking at the *Mobility* coefficients, results suggest that those researchers moving across institutions show a statistically significant increase in their productivity of 2% ($p<0.05$).[11] As mentioned earlier, this model specification suffers from an endogeneity problem due to both the simultaneity of the performance-mobility relationship and the past realizations of our dependent variable. To tackle this empirical challenge, we ran an OLS model with an instrumental variable (IV) specification. The first stage of Model 2, which is the main reference for the interpretation of the FE models, is reported in Table 3. As argued in our identification strategy, we expected IV *Students,* to be positively related to *Mobility*; results confirm our predictions. Model 2 in Table 2 shows the second stage of the OLS IV specification: *Mobility* coefficient is positive (+14%), as expected, but only marginally significant ($p<0.10$), suggesting that once

9 The results of this analysis are available from the authors upon request.

10 We also employ an additional instrumental variable, the interaction between Students (our original IV) and Mobility During Education (the number of different countries where each individual was educated up to the first job placement), which we believe is a valid approach to capture both university-level and individual-level variations to instruments Mobility in a Scientific Productivity equation. Results remain the same.

11 Given the log-transformation of *Scientific Productivity*, to interpret the correct size effect of *Mobility* coefficient, we computed the exponential transformation of the estimates. Therefore, 2% = exp (0.0198).

Table 1 Descriptive statistics and correlation matrix

Variable	N	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Scient_Prod_1	4139	30.87	33.43	0.00	281.00	1.00						
(2) Mobility	4489	1.37	0.61	1.00	4.00	−0.01	1.00					
(3) Prev_Prod_1	4139	30.87	33.43	0.00	281.00	0.99***	−0.05	1.00				
(4) Dept_Funds	3550	127,342	36,668	13,460	362,689	0.27***	0.14***	0.22***	1.00			
(5) Ind_Grants	4489	72,102	206,029	0	4,112,295	0.2***	0.00	0.17***	0.10***	1.00		
(6) PhD_Stud	3553	57.19	33.62	0.00	196.00	0.00	−0.03	−0.10***	0.33***	0.03	1.00	
(7) Coa_Affil	4489	2.82	2.91	0.00	52.00	0.25***	0.05***	0.23***	0.13***	0.07***	0.02	1.00

Significance level: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 2 Ordinary least squares (OLS) with fixed-effects (FE) for scientific productivity (one year lag)

Variables	(Model 1) FE no IV One-year lag	(Model 2) FE with IV One-year lag		(Model 3) Difference GMM Full Instruments One-year lag
Mobility	0.0198**	0.140*		0.112***
	(0.00868)	(0.0838)		(0.0335)
Prev_Prod_1	0.835***	0.808***		0.837***
	(0.00550)	(0.0192)		(0.00993)
Dept_Funds	5.47e−07***	7.90e−07***		4.42e−07***
	(9.96e−08)	(1.97e−07)		(1.66e−07)
Ind_Grants	3.61e−08**	3.88e−08**		−1.56e−08
	(1.72e−08)	(1.79e−08)		(3.18e−08)
PhD_Stud	−0.000109	4.52e−05		−0.000107
	(8.21e−05)	(0.000136)		(0.000100)
Coa_Affil	0.00210**	0.00221**		0.00534**
	(0.000854)	(0.000885)		(0.00209)
Constant	0.541***	0.414***		
	(0.0166)	(0.0896)		
Observations	3213	3213	Observations	2864
R-squared	0.946		Number of id	341
Number of id	348	348	Wald Chi2	20,552
id FE	YES	YES	Prob>chi2	0.000
University FE	YES	YES	No. of instruments	223
Instr. Variable	NO	YES	Hansen Test Prob > chi2	0.156
F-statistic	8410		Sargan Test Prob > chi2	0.641
Wald Chi2		2.665e+06	AR(1) Prob > z	0.000
Prob>chi2		0.000	AR(2) Prob > z	0.649

Differences in sample size in Model 3 are due to the lags

Models with IV show results for the Second-Stage. F-Statistic is significant at Prob > F = 0.000

Standard errors in parentheses, robust standard errors for AB models. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

controlling for its simultaneous nature in relation to performance, *Mobility* might suffer simultaneity bias when acting as regressor in performance equation. Despite our FE models largely support the expected positive relationship between mobility and productivity, the weaker results for the IV FE model, in fact, are not surprising either: as suggested by Roodman (2009) within-groups transformation does not eliminate dynamic panel bias, so regressor and error are still correlated after transformation (Roodman 2009, p. 103).

In particular, the source of possible bias in Model 2 estimates is that the level of individual performance in every period depends on the level of performance in the previous periods. To deal with this empirical challenge, we followed Roodman (2009), introducing *Previous Productivity* on the right side of the *Scientific Productivity* equation in each of our two FE models in Table 2. Results suggest that previous levels of performance significantly

Table 3 First stage OLS of fixed-effect model for scientific productivity

Variables	(Model 1) One-year lag
Students enrolled	0.175*
	(0.0988)
Prev_Prod_1	0.191***
	(0.0307)
Dept_Funds	− 1.98e−06***
	(6.18e−07)
Ind_Grants	− 3.29e−08
	(3.24e−08)
PhD_Stud	− 0.00142***
	(0.000354)
Coa_Affil	− 0.00112
	(0.00216)
Constant	− 0.589
	(0.929)
Observations	3276
Number of id	349
R-squared	0.164
id FE	YES
Uni FE	YES
F-statistic	15.32

Robust std. errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$; F-Statistic is significant at Prob > F=0.000

and strongly predict a positive variation in individual performance, as expected.[12] Despite the IV specification, and considering the presence of *Previous Productivity* in the model, this operationalization still implies possible bias introduced by autocorrelation in the FE models with IV specification. To counteract this, we employed a dynamic panel-data (DPD) estimation based on the Arellano–Bond (1991) model. Model 3 shows the Arellano–Bond estimates (difference-GMM model).

Looking at Model 3 in Table 2, the estimate of the coefficient associated to *Mobility* is positive and statistically significant ($p<0.001$), which implies that inter-organizational mobility increases individual performance (i.e., *Scientific Productivity*). More precisely, moving to a new institution is associated with an 11% increase in performance.

Our main motivation behind the Arellano–Bond choice for the empirical strategy is the presence of autocorrelation of the residuals. By construction, the residuals of the difference-GMM equation should possess serial correlation. Yet, if the assumption of serial independence in the original errors is warranted, the differenced residuals should not exhibit significant AR(2) behavior. In fact, the test for first-order serial correlation AR(1) rejects serial correlation in differences ($z=-10.34$), and the test for second-order serial correlation AR(2) does not reject serial correlation in levels ($z=0.45$). Therefore,

[12] Same results are held also when we introduce *Previous Productivity* in t-2 either in substitution to or along with *Previous Productivity* in t − 1.

Arellano–Bond seems to be a correct specification for our estimation procedure, and it successfully models the autocorrelation in our panel data. Regarding the test of exogeneity of the instruments generated in Model 3, the results of the Sargan test and Hansen test suggest we cannot reject that our instruments are exogenous (respectively $\mathrm{Prob} > \mathrm{Chi}^2 = 0.641$ and $\mathrm{Prob} > \mathrm{Chi}^2 = 0.156$).[13]

Overall, the results suggest that our empirical strategy appropriately models both the endogeneity issue of the relationship between *Mobility* and *Scientific Productivity*, as well as the autocorrelation challenges generated by estimating models with lagged dependent variables as predictors. After modeling these significant sources of bias, our estimates reflected a positive relationship between the number of individual mobility events in a specific carrier and the count of publications of each individual over time, thereby implying that academics experience a gain in productivity after moving to a new university[14] and confirming Hypothesis 1.

We also want to explore the role of resources in influencing the relationship between mobility and productivity. To test if academics moving to better-endowed departments experience a higher gain in productivity than academics moving to same or less-endowed departments, we ideally would like to know what would happen to the scientific performance of an individual moving to a department with more resources than his or her department of origin, compared to the case in which the same researcher moves to a department with less resources. Of course, this is not possible in reality, as individuals can experience only one state of the world in any given time. We therefore employed a non-parametric matching technique to construct our sample to make this comparison. Matching techniques are usually applied to evaluate the effect of a certain treatment (for example, the administration of a drug) on the sub-population of individuals exposed to the treatment (treated) and the sub-population not exposed (non-treated) (Heckman et al. 1998). The idea behind the matching estimator technique was to match each researcher moving to a "richer" department (compared to the department of origin) with a researcher presenting similar observable characteristics (including productivity pre-move) but moving to a "poorer" department, and to compare the scientific productivity after the move for the two sub-samples of individuals. We measured departmental resources as the total amount of funding received by a department from all possible sources (public and private) in a given year. These data are available through the records of the Research Assessment Exercises (RAE) in 2001 and 2008. We characterized researchers as moving to a department with more resources (*move_up*) if after their move they became affiliated with a department endowed

13 Roodman (2009) offers an additional test for exogeneity for subsets of instruments. The first subset of instruments is composed of all the instruments for each time period, variable, and lag distance, but not for the set of variables that serve as standard instruments; the test suggests we cannot reject the exogeneity of this subset of instruments ($\mathrm{Prob} > \mathrm{Chi}^2 = 0.156$). The second subset of instruments is composed by the standard instruments IV model in the specification; the test related to this second subset suggests that we cannot reject the exogeneity of this subset either ($\mathrm{Prob} > \mathrm{Chi}^2 = 0.641$).

14 Our results differ from a recent contribution looking at British researchers in physical sciences (Fernandez-Zubieta et al. 2016), which does not find a statistically significant effect of mobility on performance. We believe this discrepancy to be largely due to a different construction of the sample, as Fernandez-Zubieta and colleagues use a group of researchers which have been awarded at least one grant from the EPSRC, while we do not condition our sample on receiving a grant. When we run our model for the subset of the researchers in our sample who obtained at least one grant from the BBSRC (the equivalent of the EPSRC for biological sciences) we are able to replicate the results from Fernandez-Zubieta and colleagues. We believe our sample is better suited to show the effect of mobility on performance for a larger variety of individuals, and not just star performers.

Table 4 Effect of moving to departments with more resources

Group	Publications_ByInst			Publications_Difference		
	Mean	SE	SD	Mean	SE	SD
One match						
Move_up = 1	3.67	0.24	2.17	2.64	0.24	2.85
Move_up = 0	3.25	0.18	2.98	1.37	0.17	2.02
Difference	0.42	0.21	2.64	1.26	0.26	3.21
H_a: mean(diff) < 0	Pr(T < t) = 0.026			Pr(T < t) = 0.000		
Two matches						
Move_up = 1	3.63	0.18	3.02	2.61	0.17	2.87
Move_up = 0	3.42	0.13	2.27	1.34	0.12	2.03
Difference	0.22	0.16	2.69	1.27	0.20	3.32
H_a: mean(diff) < 0	Pr(T < t) = 0.089			Pr(T < t) = 0.000		
Three matches						
Move_up = 1	3.67	0.15	3.01	2.61	0.14	2.86
Move_up = 0	3.46	0.11	2.24	1.42	0.10	2.11
Difference	0.21	0.13	2.68	1.2	0.16	3.29
H_a: mean(diff) < 0	Pr(T < t) = 0.050			Pr(T < t) = 0.000		

with a (strictly) higher amount of funding than their department of origin. To perform the matching, we applied a nearest-neighbor matching procedure (Abadie et al. 2004), which matched each researcher moving to a richer department to the nearest researcher moving to a poorer department. We opted for this technique over the propensity score matching method (Rosenbaum and Rubin 1983), as it does not require specificity and estimates of a model describing the selection mechanism, while allowing for heteroskedastic errors. This method grants flexibility to set multiple nearest neighbors for each treated observation. Matching one researcher moving to a richer department with only one researcher moving to a poorer department minimizes the bias because that only matches the two most similar researchers. However, using more than one match decreases the variance because more information is used to derive the counterfactual for each researcher. Therefore, we reported the results of the matching estimators using one, two, and three matches. This matching technique also required we choose the vector of the covariates used to perform the matching. Given the characteristics of scientific productivity along the life-cycle of researchers (Levin and Stephan 1997), it is very important to compare individuals at the same point in their careers. We therefore used *Academic Age* (number of years elapsed since obtaining a Ph.D. degree) as a matching variable. Moreover, as past productivity is a strong predictor of future performance, we matched researchers on *Previous Productivity* (the cumulative number of publications) up to the year of the move. Once we performed the matching procedure, we compared researchers' changes in productivity using two variables. One variable (*Publications_ByInst*) indicates how many publications (on average) researchers cumulated while being affiliated with a specific institution. The second variable (*Publications_Difference*) measures the difference between the average number of publications they had in the department of origin compared to the average number of publications they had in the department of destination.

Table 4 presents the results of the test. Because the two dependent variables are normally distributed, we performed a standard *t* test of equality of means. Using samples with one, two, or three matches and the two different dependent variables, our results suggest that researchers moving to the departments with more research funds experience a statistically significant increase in productivity compared to their colleagues moving to departments with less (or the same amount) of funds. In particular, researchers moving to a richer department may expect to produce, on average, between 1.2 (three matches) and 1.27 (two match) publications more per year in their new university, compared to researchers moving to poorer departments. And, on average they tend to cumulate between 0.21 (three matches) and 0.42 (one match) more publications per year. We can therefore support the idea that moving towards better-endowed environments is a valid mechanism to explain the positive relationship between mobility and individual performance, as stated in Hypothesis 2.

4.2 Main effect: robustness checks

The main effects of the *Mobility-Scientific Productivity* relationship could have been sensitive to three aspects of our variable construction.

First, we used one-year lag for *Scientific Productivity*. One could expect that results might change, depending on the lag applied to our dependent variable. This would be the case if one believes that producing an academic publication in biology takes less than a year, and therefore individual performance should be measured in the same year of the mobility event. Conversely, if one believes it takes more than 1 year to produce a publication, a two-year lag is needed. Replicating the models in the main specification using nor lag or a two-year lag produces qualitatively consistent results.

Second, we used publication counts to operationalize *Scientific Productivity*. One can argue that this measure refers only to the quantity of the academic scientific output, and it does not consider the quality of such output. Perhaps, producing greater quantity does not necessarily equal producing better quality. In this case, our operationalization of *Scientific Productivity* would only partially capture the individual performance in one of its dimensions. To counteract this, we checked to see whether or not our models would provide different empirical evidences if we used *Citations*, a count of citations in every year related to the focal researcher's published work, instead of publication count. We combined this sensitivity test on operationalization of performance with the previous point on lags specifications. Appendix 2 shows results for all models with *Citations* as dependent variable, and *Scientific Productivity* specified as no-year lag, one-year-lag, and two-year lag. The coefficients replicate at large the results of our main model in Table 2.

Third, one can argue that the count of publications is not strictly a productivity measure, but rather a measure of output, in particular quantity. In order to deal with this possible interpretation of the operationalization of our dependent variable, we generated *Scientific Productivity by Age* (Scient_Prod), as the ratio between *Scientific Productivity* (in publications) and *Academic Age* (number of years elapsed since obtaining a Ph.D. degree). Results remain the same.

We can therefore conclude that our results seem to be consistent and robust across multiple variable operationalization procedures and multiple model specifications, granting additional support to the conclusions from our main models.

5 Discussion and conclusion

In this paper, we explored the question of whether mobility affects individual productivity in the context of academic scientists. We theorize that post-mobility performance is shaped by three different interacting forces: positive treatment effects reflecting knowledge spillovers and improved employee matching, negative treatment effects reflecting disruption of routines and loss of firm- and relationship-specific human capital, and positive selection effects reflecting worker autonomy when voluntarily choosing to move. We then examined the cumulative effect of these three forces on post-mobility performance.

Examining academic scientists allows observing meaningful and quantifiable knowledge production outcomes over time, as measured by peer-refereed publications. Publications in peer-refereed journals can be evaluated following widely accepted and objective measures, drastically reducing the production causal ambiguity observed in the context of other knowledge-intensive industries. Also, one of the most salient characteristics of the university environment and academic research is that academics possess human capital that is unlikely to be organization-specific and is therefore, easily transportable and usable across organizations. Additionally, academic scientists have great autonomy over with whom they work and on which projects they work and are members of durable communities that span organizational boundaries. Finally, in the specific national context used in this study (the United Kingdom), academic researchers face a very fluid labor market, characterized by the absence of a tenure system and by the fact that academic salaries tend to vary within a well-defined national-range, thus presenting low barriers to mobility and providing a setting where mobility events are common and easily observable.

In this context, the cumulative effect of the three forces suggested that researchers experience a productivity boost when they move and this boost is positively moderated by the resources of the destination university. We tested these hypotheses on a sample of bioscience academics in the UK between 1995 and 2009 for our empirical analysis using an instrumental variable approach and a dynamic panel data specification. The empirical results suggested strong support for our hypotheses.

With this work, we attempted to address important issues that have influenced the results obtained so far in studies on talented employees' mobility. First, we contribute to the literature in the economics of science on the determinants of scientific productivity. While many individual (age, gender, position, discipline of affiliation) and organizational (quality of the institution, size of the institution, peers' productivity) characteristics are related to researchers' productivity (Azoulay et al. 2010; Stephan 1996), only a few studies have focused on the effect of mobility (Fernandez-Zubieta et al. 2016). In our analysis, we show that even after taking into account individual characteristics, highly mobile academics tend to increase their productivity, especially when they move to universities with more resources or where their co-authors already work.

Second, we make an empirical contribution by trying to address the issue of endogeneity caused by the bi-directional nature of the relationship between mobility and performance. Following recent efforts in the literature to explain such endogeneity (Fernandez-Zubieta et al. 2016; Groysberg et al. 2008; Hoisl 2007; Singh and Agrawal 2011), we attempted to appropriately model the effect of mobility on individual performance. While we acknowledge the simultaneity between these two variables, our paper aims at analyzing only one direction of the relationship: mobility as an antecedent of performance. To identify our model correctly, we employed an instrumental variable—the number of students enrolled in the university of destination—which we argue affects mobility but not

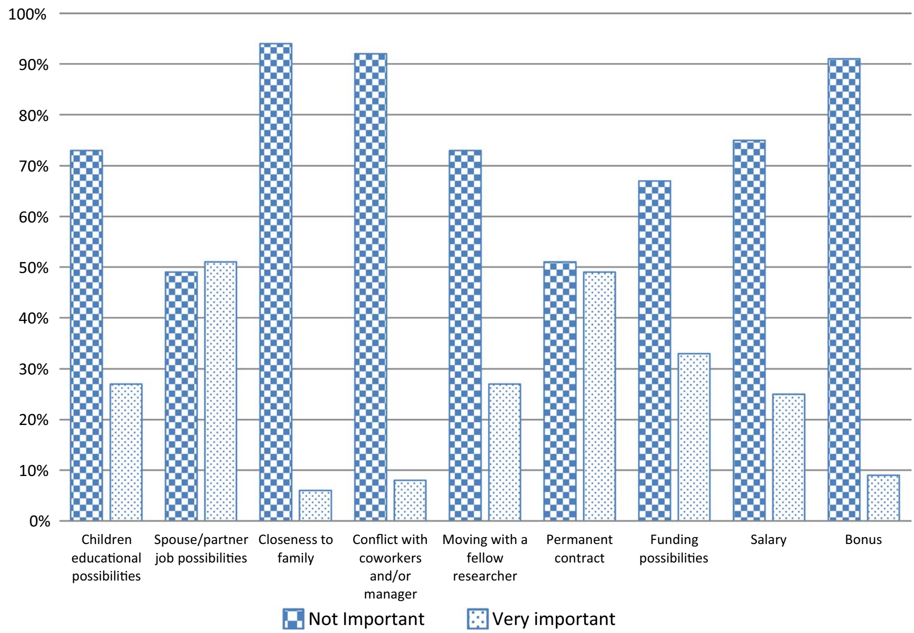

Fig. 2 Reasons for moving

scientific productivity. Taking advantage of the balanced panel structure of our data, we employed Arellano–Bond GMM estimators to model the autocorrelation issues generated by the dynamic nature of scientific productivity.

Notwithstanding the effort made in modeling endogeneity, both through instrumental variables and matching procedures, we cannot ignore the fact that mobility is never happening randomly. To further address with issue, we have administered an exploratory questionnaire to all the researchers in our sample who experienced at least one mobility event (N = 155). The survey was administered via email, and we have obtained 60 responses, corresponding to 39% response rate. In the survey we asked respondents to inform us on the reasons behind their choice to move from one university to another. We presented them with the names of their institution of origin (A) and their institution of destination (B) and asked on a 5-point Likert scale ranging from *Not at all important* to *Very important*, how important were a series of reasons for their choice to move from A to B. We grouped reasons into four classes: family, personal/social reasons at work, funding, financial reasons. Figure 2 shows the responses for all the items.

First of all, it is important to note that among the family reasons, job possibilities of partners seem to be highly relevant in relation to the mobility choices of researchers. This aspect is very often under-investigated in the literature on mobility of highly-skilled individuals, while it may represent one of the main reasons or barriers of cross-organizational mobility of individuals. Second, one may worry that our positive effect on performance is a result of individuals moving from institutions where they were exposed to conflicts or disagreements with their co-workers or superiors. This does not seem to be the case in our sample, further supporting the assumption that we are indeed observing voluntary mobility. Third, it seems that mobility is very often related to appropriation of rent, not in terms of salary (which is often not subject to wide negotiations) but in terms of better positions or promotions. Finally, we observe that funding possibilities in the university of destination do not seem to be an important reason behind mobility. This observation reinforces our results that highlight the importance of funding for productivity (as funds are generally personal) rather than for mobility.

Our final contribution focuses on the more general understanding of the conditions under which we can expect the relationship between mobility and individual performance to be positive or negative. We believe that specific environmental and organizational factors play a fundamental role in shaping the forces that drive post-mobility performance for employees who voluntarily choose to move. Therefore, the choice of context of analysis becomes crucial in determining what kind of effect we will likely observe in the data, ultimately affecting our theoretical understanding of the phenomenon. By relaxing some of the assumptions deriving from specific contextual factors in knowledge-intensive industries, e.g., semiconductors or pharmaceuticals, which are usually the subject of empirical research on employees' mobility, we made predictions in a context in which knowledge assets represented by the individual human capital are less embedded in the organizational routines, thus facilitating less post-mobility disruption and a stronger cumulative effect and consequently resulting in a positive relationship between inter-organizational mobility and individual performance.

Notwithstanding the effort we put into modeling the relationship between mobility and individual performance, results need to be interpreted taking into account the limitations of our study, which in turn opens possibilities for future research. First, our model only investigated one direction of the mobility-productivity relationship. As we recognize the inherent bi-directionality of this relationship, future research should further investigate both directions to assess not only the impact of mobility on performance, but also how performance influences the likelihood of individuals moving in the first place.

Second, our paper attempted to model potential endogeneity biases of the research stream on mobility. In this sense, IV and Arellano–Bond empirical strategies seem to be appropriate for meeting the empirical challenges mentioned. While our econometric results and preliminary evidence from a survey confirmed our empirical strategy as valid, future research should continue to explore currently developed empirical strategies such as matching estimators and difference-in-difference estimators (Azoulay et al. 2010; Groysberg et al. 2008; Singh and Agrawal 2011) to improve the precision in the estimation process and the related interpretation. This is especially relevant when it comes to modeling the unobserved heterogeneity typical of the research on mobility in innovative contexts, where the scarcity of data presents important challenges to any empirical researcher interested in this field. We also think that a deeper analysis of the motivations behind individuals' choice of changing employers will greatly improve our understanding of the mechanisms behind mobility events.

Third, our analysis highlighted how the characteristics of the context of study influence the sign of the relationship between mobility and performance; in particular, we discussed the role of portability of assets in determining if individuals can ultimately benefit from moving across organizations. Future research should focus on industries where the portability of such assets can be modulated by firms in order to fully understand its implications for individuals and also organizational performance.

Appendix 1

See Table 5.

Table 5 Distribution of CVs collected per university

Institution	# of researchers	# of CV collected	% response
Imperial College London	79	57	72
University College London	125	73	58
University of Birmingham	53	28	53
University of Cambridge	229	75	33
University of Edinburgh	177	87	49
University of Glasgow	85	49	58
University of Oxford	278	40	14
Total	1026	409	40

Appendix 2

See Table 6.

Table 6 OLS with fixed-effects and Arellano–Bond two-step difference GMM with different lags for citations

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)		(Model 7)	(Model 8)	(Model9)
	FE no IV	FE with IV	FE no IV	FE with IV	FE no IV	FE with IV		Diff. GMM	Diff. GMM	Diff. GMM
Variables	No Lag	No Lag	1Y Lag	1Y Lag	2Y Lag	2Y Lag		No Lag	1Y Lag	2Y Lag
Mobility	0.168***	1.525***	0.0930***	0.991***	0.0404**	0.482***		0.183*	0.127*	0.0954
	(0.0298)	(0.314)	(0.0244)	(0.227)	(0.0198)	(0.156)		(0.108)	(0.0705)	(0.0606)
Dept_Funds	0.598***	0.465***						0.671***		
	(0.00826)	(0.0322)						(0.0283)		
Ind_Grants	3.44e−06***	5.54e−06***	2.97e−06***	4.34e−06***	1.07e−06***	1.72e−06***		2.10e−06***	1.54e−06***	− 1.31e−07
	(3.15e−07)	(6.35e−07)	(2.61e−07)	(4.67e−07)	(2.15e−07)	(3.24e−07)		(6.13e−07)	(4.43e−07)	(3.57e−07)
PhD_Stud	1.33e−07**	1.08e−07	9.60e−08**	7.91e−08	6.72e−08*	5.72e−08		1.26e−07	− 3.07e−09	− 7.43e−08
	(5.88e−08)	(7.71e−08)	(4.80e−08)	(5.84e−08)	(3.90e−08)	(4.25e−08)		(8.65e−08)	(8.34e−08)	(7.85e−08)
Coa_Affil	0.000246	0.00221***	0.000204	0.00151***	7.60e−05	0.000742**		− 0.000169	0.000215	− 0.000108
	(0.000278)	(0.000578)	(0.000231)	(0.000432)	(0.000191)	(0.000312)		(0.000226)	(0.000257)	(0.000172)
Prev_Cit_0	0.0359***	0.0340***	0.00325	0.00534*	0.000102	0.000395		0.0218***	0.00621	− 0.00703**
	(0.00291)	(0.00383)	(0.00242)	(0.00299)	(0.00198)	(0.00215)		(0.00637)	(0.00650)	(0.00345)
Prev_Cit_1			0.653***	0.539***					0.734***	
			(0.00910)	(0.0308)					(0.0250)	
Prev_Cit_2					0.738***	0.672***				0.820***
					(0.00922)	(0.0250)				(0.0305)
Constant	1.984***	0.569*	1.921***	1.183***	1.725***	1.444***				
	(0.0571)	(0.333)	(0.0529)	(0.196)	(0.0516)	(0.113)				
Obs.	3276	3276	3213	3213	3142	3142		2926	2864	2799
No. of id	0.798		0.797		0.815			347	341	334
id FE	349	349	348	348	342	342	Wald Chi2	5889	7931	7571
Uni FE	YES	YES	YES	YES	YES	YES	Prob>chi2	0.000	0.000	0.000
Instr. Var.	YES	YES	YES	YES	YES	YES	No. of instr.	223	223	223
F-statistic	NO	YES	NO	YES	NO	YES	Hansen Test Prob > chi2	0.0862	0.264	0.480

Table 6 (continued)

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)		(Model 7)	(Model 8)	(Model9)
	FE no IV	FE with IV	FE no IV	FE with IV	FE no IV	FE with IV		Diff. GMM	Diff. GMM	Diff. GMM
Variables	No Lag	No Lag	1Y Lag	1Y Lag	2Y Lag	2Y Lag		No Lag	1Y Lag	2Y Lag
Wald Chi2	1920		1872		2049		Sargan Test Prob > chi2	0.998	0.992	0.870
Prob>chi2		613,827		1.117e+06		2.175e+06	AR(1) Prob > z	2.78e−10	7.09e−10	6.63e−06
							AR(2) Prob > z	0.525	0.0860	0.187

Models with IV show results for the Second-Stage. F-Statistic is significant at Prob > F = 0.000. Differences in sample size are due to the lag

Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

References

Abadie, A., Drukker, D., Leber Herr, J., & Imbens, G. W. (2004). Implementing matching estimators for average treatment effects in stata. *Stata Journal, 4*(3), 290–311.

Aghion, P., Dewatripont, M., & Stein, J. C. (2008). Academic freedom, private-sector focus, and the process of innovation. *The Rand Journal of Economics, 39*(3), 617–635. https://doi.org/10.1111/j.1756-2171.2008.00031.x.

Aime, F., Johnson, S., Ridge, J. W., & Hill, A. D. (2010). The routine may be stable but the advantage is not: Competitive implications of key employee mobility. *Strategic Management Journal, 31*(1), 75–87. https://doi.org/10.1002/smj.809.

Aksnes, D. W., Rørstad, K., Piro, F. N., & Sivertsen, G. (2013). Are mobile researchers more productive and cited than non-mobile researchers? A large-scale study of Norwegian scientists. *Research Evaluation, 22*(4), 215–223. https://doi.org/10.1093/reseval/rvt012.

Almeida, P., Hohberger, J., & Parada, P. (2011). Individual scientific collaborations and firm-level innovation. *Industrial and Corporate Change*, dtr030. https://doi.org/10.1093/icc/dtr030.

Allison, P. D, Long, J. S. (1990). Departmental effects on scientific productivity. *American Sociological Review, 55*(4), 469–478.

Archambault, É., Campbell, D., Gingras, Y., & Larivière, V. (2009). Comparing bibliometric statistics obtained from the Web of Science and Scopus. *Journal of the American Society for Information Science and Technology, 60*(7), 1320–1326. https://doi.org/10.1002/asi.21062.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277–297. https://doi.org/10.2307/2297968.

Audretsch, D. B., Bozeman, B., Combs, K. L., Feldman, M., Link, A. N., Siegel, D. S., et al. (2002). The economics of science and technology. *The Journal of Technology Transfer, 27*(2), 155–203. https://doi.org/10.1023/A:1014382532639.

Azoulay, P., Zivin, J. S. G., & Wang, J. (2010). Superstar extinction. *The Quarterly Journal of Economics, 125*(2), 549–589.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108.

Borjas, G. J., & Doran, K. B. (2012). The collapse of the soviet union and the productivity of American mathematicians*. *The Quarterly Journal of Economics, 127*(3), 1143–1203. https://doi.org/10.1093/qje/qjs015.

Campbell, B. A., Coff, R., & Kryscynski, D. (2012a). Rethinking sustained competitive advantage from human capital. *Academy of Management Review, 37*(3), 376–395. https://doi.org/10.5465/amr.2010.0276.

Campbell, B. A., Di Lorenzo, F., & Tartari, V. (2018). *Cross-organization collaboration and mobility of knowledge workers*.

Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012b). Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal, 33*(1), 65–87. https://doi.org/10.1002/smj.943.

Campbell, B. A., Kryscynski, D., & Olson, D. M. (2017). Bridging strategic human capital and employee entrepreneurship research: A labor market frictions approach. *Strategic Entrepreneurship Journal, 11*(3), 344–356. https://doi.org/10.1002/sej.1264.

Cañibano, C., & Bozeman, B. (2009). Curriculum vitae method in science policy and research evaluation: The state-of-the-art. *Research Evaluation, 18*(2), 86–94. https://doi.org/10.3152/095820209X441754.

Cañibano, C., Otamendi, J., & Andújar, I. (2008). Measuring and assessing researcher mobility from CV analysis: The case of the Ramón y Cajal programme in Spain. *Research Evaluation, 17*(1), 17–31. https://doi.org/10.3152/095820208X292797.

Carnahan, S., Agarwal, R., & Campbell, B. A. (2012). Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers. *Strategic Management Journal, 33*(12), 1411–1430. https://doi.org/10.1002/smj.1991.

Chiang, S.-H., & Chiang, S.-C. (1990). General human capital as a shared investment under asymmetric information. *The Canadian Journal of Economics/Revue canadienne d'Economique, 23*(1), 175–188. https://doi.org/10.2307/135526.

Coff, R. W. (1997). Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. *Academy of Management Review, 22*(2), 374–402. https://doi.org/10.5465/AMR.1997.9707154063.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. (2000). *Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not)* (Working Paper No. 7552). National Bureau of Economic Research. http://www.nber.org/papers/w7552. Accessed 8 September 2016

Corredoira, R. A., & Rosenkopf, L. (2010). Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal, 31*(2), 159–181. https://doi.org/10.1002/smj.803.

Crane, D. (1972). *Invisible colleges, diffusion of knowledge in scientific communities*. Chicago: University of Chicago Press.

Cruz-Castro, L., & Sanz-Menéndez, L. (2010). Mobility versus job stability: Assessing tenure and productivity outcomes. *Research Policy, 39*(1), 27–38. https://doi.org/10.1016/j.respol.2009.11.008.

De Filippo, D., Casado, E. S., & Gomez. (2009). Quantitative and qualitative approaches to the study of mobility and scientific performance: a case study of a Spanish university, *18*(3), 191–200.

De Solla Price, D. (1986). *Little science, big science…and beyond*. New York: Columbia University Press.

Deloitte. (2012). *University Staff Academic Salaries and Remuneration*. http://www.universitiesnz.ac.nz/node/276.

Di Lorenzo, F., & Almeida, P. (2017). The role of relative performance in inter-firm mobility of inventors. *Research Policy, 46,* 1162–1174. https://doi.org/10.1016/j.respol.2017.05.002.

Dokko, G., & Rosenkopf, L. (2009). Social capital for hire? Mobility of technical professionals and firm influence in wireless standards committees. *Organization Science, 21*(3), 677–695. https://doi.org/10.1287/orsc.1090.0470.

Drucker, P. F. (1998). *Peter Drucker on the profession of management*. Boston: Harvard Business Press.

Ernst, H., & Vitt, J. (2000). The influence of corporate acquisitions on the behaviour of key inventors. *R&D Management, 30*(2), 105–120. https://doi.org/10.1111/1467-9310.00162.

Feldman, M. P., Link, A. N., & Siegel, D. S. (2012). *The economics of science and technology: An overview of initiatives to foster innovation, entrepreneurship, and economic growth*. Berlin: Springer Science & Business Media.

Fernandez-Zubieta, A., Geuna, A., & Lawson, C. (2015). *What do we know of the mobility of research scientists and of its impact on scientific production* (SSRN Scholarly Paper No. ID 2611203). Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2611203. Accessed 26 August 2015.

Fernandez-Zubieta, A., Geuna, A., & Lawson, C. (2016). Productivity pay-offs from academic mobility: should I stay or should I go? *Industrial and Corporate Change, 25*(1), 91–114. https://doi.org/10.1093/icc/dtv034.

Franzoni, C., Scellato, G., & Stephan, P. (2014). The mover's advantage: The superior performance of migrant scientists. *Economics Letters, 122*(1), 89–93. https://doi.org/10.1016/j.econlet.2013.10.040.

Gambardella, A., Giarratana, M. S., & Panico, C. (2010). How and when should companies retain their human capital? Contracts, incentives and human resource implications. *Industrial and Corporate Change, 19*(1), 1–24.

Geuna, A., Kataishi, R., Toselli, M., Guzmán, E., Lawson, C., Fernandez-Zubieta, A., et al. (2015). SiSOB data extraction and codification: A tool to analyze scientific careers. *Research Policy, 44*(9), 1645–1658. https://doi.org/10.1016/j.respol.2015.01.017.

Groysberg, B., Lee, L.-E., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge workers' performance. *Management Science, 54*(7), 1213–1230. https://doi.org/10.1287/mnsc.1070.0809.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica, 50*(4), 1029–1054. https://doi.org/10.2307/1912775.

Hagstrom, W. O. (1997). Inputs, outputs, and the prestige of university science departments. *Sociology of Education, 44*(4), 375–397.

Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies, 65*(2), 261–294. https://doi.org/10.1111/1467-937X.00044.

HEFCE. (2011). *Higher education-business and community interaction survey 2009–2010*. Higher Education Council Funding for England.

Hoffman, P. (1999). *The man who loved only numbers: The story of Paul Erdos and the search for mathematical truth*. Hyperion Books.

Hoisl, K. (2007). Tracing mobile inventors—The causality between inventor mobility and inventor productivity. *Research Policy, 36*(5), 619–636. https://doi.org/10.1016/j.respol.2007.01.009.

Jovanovic, B. (1979). Job matching and the theory of turnover. *Journal of Political Economy, 87*(5), 972–990.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science, 3*(3), 383–397. https://doi.org/10.1287/orsc.3.3.383.
Levin, S. G., & Stephan, P. E. (1997). The critical importance of careers in collaborative scientific research. *Revue d'économie industrielle, 79*(1), 45–61. https://doi.org/10.3406/rei.1997.1652.
Lissoni, F., Montobbio, F., & Zirulia, L. (2013). Inventorship and authorship as attribution rights: An enquiry into the economics of scientific credit. *Journal of Economic Behavior and Organization, 95,* 49–69. https://doi.org/10.1016/j.jebo.2013.08.016.
Long, J. S. (1978). Productivity and academic position in the scientific career. *American Sociological Review, 43*(6), 889–908.
Lotka, A. (1926). The frequency distribution of scientific productivity. *Journal of Washington Academy Sciences, 16,* 317–323.
Mackey, A., Molloy, J. C., & Morris, S. S. (2013). Scarce human capital in managerial labor markets. *Journal of Management*. https://doi.org/10.1177/0149206313517265.
Mahoney, J. T., & Qian, L. (2013). Market frictions as building blocks of an organizational economics approach to strategic management. *Strategic Management Journal, 34*(9), 1019–1041. https://doi.org/10.1002/smj.2056.
Mawdsley, J. K., & Somaya, D. (2016). Employee mobility and organizational outcomes an integrative conceptual framework and research Agenda. *Journal of Management, 42*(1), 85–113. https://doi.org/10.1177/0149206315616459.
Merton, R. K. (1957). Priorities in scientific discovery: A chapter in the sociology of science. *American Sociological Review, 22*(6), 635–659. https://doi.org/10.2307/2089193.
Merton, R. K. (1968). The matthew effect in science: The reward and communication systems of science are considered. *Science, 159*(3810), 56–63.
Merton, R. K. (1973). The sociology of science. *Theoretical and empirical investigations*. Chicago: University of Chicago Press
Moser, P., Voena, A., & Waldinger, F. (2014). *German-Jewish Emigres and US invention* (Working Paper No. 19962). National Bureau of Economic Research. http://www.nber.org/papers/w19962. Accessed 26 August 2015.
Mustar, P., & Wright, M. (2009). Convergence or path dependency in policies to foster the creation of university spin-off firms? A comparison of France and the United Kingdom. *The Journal of Technology Transfer, 35*(1), 42–65. https://doi.org/10.1007/s10961-009-9113-7.
Nakajima, R., Tamura, R., & Hanaki, N. (2010). The effect of collaboration network on inventors' job match, productivity and tenure. *Labour Economics, 17*(4), 723–734. https://doi.org/10.1016/j.labeco.2009.11.006.
OECD. (2010). *Science, technology and industry outlook*.
Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., et al. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. *Research Policy, 42*(2), 423–442. https://doi.org/10.1016/j.respol.2012.09.007.
Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal, 14*(3), 179–191. https://doi.org/10.1002/smj.4250140303.
Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal, 9*(1), 86–136.
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41.
Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science, 49*(6), 751–766. https://doi.org/10.1287/mnsc.49.6.751.16026.
Scopus Info. (2013). *Scopus content overview*. Elsevier. http://www.elsevier.com/online-tools/scopus/content-overview.
Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science, 57*(1), 129–150. https://doi.org/10.1287/mnsc.1100.1253.
Slavova, K., Fosfuri, A., & De Castro, J. O. (2015). Learning by hiring: The effects of scientists' inbound mobility on research performance in Academia. *Organization Science, 27*(1), 72–89. https://doi.org/10.1287/orsc.2015.1026.
Somaya, D., Williamson, I. O., & Lorinkova, N. (2008). Gone but not lost: The different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal, 51*(5), 936–953. https://doi.org/10.5465/AMJ.2008.34789660.
Stephan, P. E. (1996). The economics of science. *Journal of Economic Literature, 34*(3), 1199–1235.
Stern, S. (2004). Do scientists pay to be scientists? *Management Science, 50*(6), 835–853. https://doi.org/10.1287/mnsc.1040.0241.

Van Heeringen, A., & Dijkwel, P. (1987). The relationships between age, mobility and scientific productivity. *Part I. Scientometrics, 11*(5–6), 267–280. https://doi.org/10.1007/BF02279349.

Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany. *The Review of Economic Studies, 79*(2), 838–861. https://doi.org/10.1093/restud/rdr029.

Wezel, F. C., Cattani, G., & Pennings, J. M. (2006). Competitive implications of interfirm mobility. *Organization Science, 17*(6), 691–709. https://doi.org/10.1287/orsc.1060.0219.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science, 316*(5827), 1036–1039. https://doi.org/10.1126/science.1136099.