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Productivity pay-offs from academic mobility: should I stay or should I go?

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Abstract

This article analyses the impact of interorganizational mobility on academic performance. We develop a theoretical framework based on the job-matching approach adapted for researchers. The empirical analysis studies the careers of a sample of 171 UK academics, spanning 1957–2005. We find no evidence that mobility per se increases academic performance. Only mobility to "better" departments has a positive weakly significant impact, while downward mobility reduces researchers' productivity. Job mobility is always associated with a short-term decrease in performance.

JEL classification: O31, I23, J24

1. Introduction[1]

The UK university system has undergone a major restructuring since the 1980s. Starting from the introduction of the Research Assessment Exercise in 1986, policy action has driven the system toward higher levels of concentration of research resources in a small number of research-intensive universities (DES, 1991; HEFCE, 1997; DfES, 2003; BIS, 2009). Concentration and selectivity policies have created a market for academics, and increased mobility of permanent full-time scientists (DfES, 2003). Interorganizational mobility of researchers has been seen as a positive by-product of policy action, to be directly supported (HEFCE, 1997).[2] Data from the Higher Education Statistical Agency spanning the period 1994–1995 to 2005–2006 (the last year included in our database of UK scientists) show almost a doubling in the share of full-time academics changing employment, with some 2600 academics changing jobs in 1994–1995 and about 5100 in 2005–2006.

1 The data and framework introduced in this article are also used in Fernandez-Zubieta et al. (2015a) companion paper.
2 See Universities UK (2009) for an analysis of increased concentration of resources in the UK system in the period 1994–2007.

Interorganizational mobility can give rise to both social and individual productivity returns. Researcher mobility could be a mechanism of knowledge diffusion and generate positive spillovers between firms, sectors, institutions, and countries. By increasing the diffusion of ideas, researcher mobility may be positive for the research system as a whole. A few papers analyze these socially relevant benefits by focusing on the spillover effect of mobility among firms (Pakes and Nitzan, 1983; Cooper, 2001; Møen, 2005), sectors (Zucker et al., 1998; Crespi et al., 2007; Azoulay et al., 2012), and academic institutions and countries (Moser et al., 2014; Borjas and Doran, 2012). More systematic investigation is still required to properly understand the social returns of academic mobility.

Even less is known for the case of individual productivity returns to academic mobility. We know little about the benefits (or costs) associated to the decision of a scientist to move to a new job in a different university. This article tries to fill this gap by assessing whether and how mobility to another university affects researchers' publication productivity. We thus ask from the perspective of individual scientific performance, whether a scientist should stay or should go to a new university? A few papers in the sociology of science (see e.g. Allison and Long, 1990, and much earlier Hargens and Farr, 1973) study this topic and find some weak evidence of a negative impact of immobility and some suggestion that job mobility is a characteristic of productive researchers (Allison and Long, 1987; van Heeringen and Dijkwel, 1987). Some attention has also been devoted to the relationship between individual research productivity and international scientific mobility both at postdoctoral level (Cañibano et al., 2008; Zubieta, 2009; Horta et al. 2010; Franzoni et al., 2012) and in general (Stephan and Levin, 2001; Hunter et al., 2009; Stephan, 2012; Franzoni et al., 2012). However, due to unavailability of data and difficulties related to controlling for endogeneity bias, these studies offer only limited insights into the relationship between mobility and productivity.

We develop a theoretical framework to predict the impact of job mobility on research productivity, based on a job-matching approach to academic labor mobility that emphasizes research and reputation factors. The idea that productivity is driven by the availability of capital equipment (and human capital) for research and peer effects leads us to expect medium-term positive effects on productivity only for job changes that imply a move to a higher quality/reputation institution. In our framework, a job change is associated always with a short-term reduction in productivity due to mobility and adjustment costs.

We test the predictions of the theoretical framework with information about the entire careers of a sample of mobile and nonmobile researchers. We estimate a series of econometric specifications of our model in a dynamic setup, to assess the impact of job changes on post-mobility output. To address the problem of endogeneity arising from reverse causality, we estimate an instrumental variables (IV) model using distance from place of birth (time invariant) and performance mismatch (time variant) as instruments. The empirical analysis is based on a unique database that includes detailed information on the employment patterns and publishing activities of a sample of UK academic researchers in science and engineering, from the year of their first professional appointment, for the period 1957–2005. The availability of reliable institution-level information on publications and citations needed to build an original time-varying research-ranking indicator, limited the econometric analysis to the 23-year period 1982–2005. Our sampling strategy includes a focus only on research-active academics occupying "tenured type" positions, that is, we do not include mobility due to nonrenewal of contract. Thus, a job change is the result of the researchers' decision.

We find no evidence that mobility per se boosts the scientific productivity of researchers; what matters is where an academic moves to. Mobility to lower-ranked universities is accompanied by a decrease in both number and impact of publications, while upward mobility is associated with a positive, weakly significant increase in productivity, but no quality effect. In both cases we find strong evidence of short-term negative effects.

2. What do we know about researchers' productivity and interorganizational mobility?

In their study of academic stars, Zucker et al. (2002) examine the case of mobile scientists, emphasizing the role of productivity for explaining mobility; this seminal study has been followed by many others. Instead, there are only few systematic studies that try to assess the other side of the relationship—whether mobility has a positive or negative impact on scientific productivity (amongst them Allison and Long, 1990), and there is no evidence that considers the causal effect between mobility and researcher productivity.

This article tries to help to fill this gap. Starting from the traditional analytical model of scientific productivity (Cole, 1979; Levin and Stephan, 1991), we study scientific productivity (*sp*) as a function of individual characteristics, environmental specificities, and mobility events:

$$sp = f(M, p, h) \tag{1}$$

where M is the mobility event, p is individual personal and academic characteristics, and h is institution-, field-, country-, and time-specific environmental characteristics affecting scientific productivity.

Job mobility may have a positive impact on research productivity only if the researcher finds better conditions for pursuing her research endeavor; for example, if she moves to a new job to increase her research performance. However, there are other traditional reasons for mobility (salary, family demands, etc.) that are unrelated to research performance. To fully understand the impact of mobility on research productivity, we need first to understand what drives researchers' mobility, and then to model the impact of mobility on performance controlling for those factors that might have a confounding effect. Below, we briefly review the main tenets in the literature on the drivers of mobility, and discuss the characteristics that distinguish the academic labor market (Section 2.1); in Section 2.2, we propose a model for academic mobility and its impact on researcher performance. In the empirical analysis, we will take into account the mobility model when we estimate the productivity equation (1).

2.1. The academic labor market: Distinctive characteristics

2.1.1 Traditional labor market factors

The academic labor market is driven by traditional labor market factors and a set of academia-specific factors related to research and reputation. The most important labor market factors are: (i) wage related—the difference between current compensation and the new wage offer; (ii) career related—promotion to associate or full professor usually associated with access to more resources for research and the possibility of hiring and directing doctoral and postdoctoral fellows; (iii) opportunity related—non-permanent academic jobs are becoming more common in all countries and are associated with termination and nonrenewal of contracts, resulting in involuntary mobility; (iv) market related—the fluidity of the job market differs across countries and disciplinary fields, and the density of the market varies depending on the time period;[3] (5) mobility cost related—the costs associated with mobility are not fixed and depend on mobility experience;[4] (6) family related—partners moving, ageing parents, and children's education are common reasons for involuntary mobility and also reduction in the propensity to move, and introduce a gender and age bias.

2.1.2 Academic distinctive mobility factors

The academic labor market is characterized by some distinctly academic factors, which are the focus of this article. In the academic labor market, research and "reputational" factors could be as, or even more, important than salary in the decision to accept or reject an offer (Levin and Stephan 1991). For academics, research (time and support) is the most important aspect of their job and yield the greatest job satisfaction while also being a work activity that produces outputs. The time spent doing research is perceived by academics as partly consumption time, resulting in a willingness to forego the higher wages available in industry jobs which do not allow independent research. Hence, all else being equal, academics are willing to earn less to be able to focus on their chosen research (Stern, 2004; Sauermann and Roach, 2013). Another important argument in the utility function of a researcher is reputation, which is affected in part by institutional reputation (to simplify we do not distinguish between department and university). A researcher values employment in a highly prestigious institution because of its direct benefits, such as more research time and higher financial endowments, but also because of the positive externalities attached to these positions which can add to individual reputation. These aspects are important in the market for scientists where individual quality assessments are not straightforward, especially in early-stage research careers, and publications are not perfect carriers of information. All else being equal, an academic will move to a higher-ranked institution (expecting

3 See the discussion of transfer markets for top scientists as a feature of the UK Research Assessment Exercise (Elton, 2000).

4 First-time mobility is the most costly (leaving home effect); multiple job changes are associated with learning from experience which decreases mobility costs (e.g., foreigners or nationals with foreign PhDs will have lower mobility costs).

the benefits to outweigh the mobility costs), since research and reputation enter positively in her utility function. In addition, institutional reputation may increase the probability of receiving future research funding; in the context of funding agencies' selection, there are more excellent proposals than available budget, and institutional reputation can matter for the final selection decision.

In addition, especially in new and fast-changing disciplines, mobility is driven by the prospect of accessing tacit knowledge and new equipment. In the early phases of development of a new discipline, knowledge is located in a small number of laboratories responsible for the original discoveries. Publications allow this knowledge to percolate through the university system, but due especially to the invention of new equipment (see e.g. the case of the production of the onco-mouse, Murray, 2010), some knowledge is "sticky" to a particular laboratory and can be passed on only via training in and use of the equipment. Researchers are willing to bear the costs of a move to these centers to acquire the tacit knowledge held there. Acquisition of tacit knowledge can be achieved through short stays (such as sabbatical leave) or job changes.

Finally, academic mobility is strongly affected by relative opportunity advantage. In a market with clear reputation/quality ranking, researchers working in high-ranked institutions have much lower probabilities of moving, all else being equal.

2.2 Modeling the relationship between mobility and researcher's scientific productivity

2.2.1 The mobility model

The relationship between mobility and researchers' scientific productivity is bidirectional. To model the impact of mobility on research productivity we need to first model the reasons of academic mobility (M). The probability of a job change (M) depends on the probability of receiving a job offer $f(\cdot)$ and the probability of accepting that job offer $g(\cdot)$. Let us define:

$$M = f(\cdot) \times g(\cdot) \text{ where } f(\cdot) = f(s, e, p) \quad \text{and} \quad g(\cdot) = (w,\ b,\ c,\ r) \tag{2}$$

The probability of receiving an offer $f(\cdot)$ is likely to depend on factors such as search effort (s), and environmental (e) and individual (p) labor characteristics. The probability of accepting an offer $g(\cdot)$ is likely to depend on the level of the wage offer (w) relative to the individual's current compensation (b), and other mobility costs (c). We modify the basic model to include the academic labor market distinctive factor (r) that takes account of the research- and reputation-related effects discussed in the previous section.

While the probability of receiving a job offer $f(\cdot)$ depends on traditional labor market factors contextualized to the academic market, the probability of accepting an offer $g(\cdot)$ takes a different form in the academic market. In academia, academic salaries tend to vary within a well-defined national range, based on experience, with some limited flexibility at the top depending on the country considered. In the US, professorial salaries can vary significantly; however, in most other countries, public employee contracts or tradition give little room for individual salary increases. In the academic labor market, this leads to a reduced effect of salary on the probability of moving. In Europe, the wage offer (w) relative to the individual's current compensation (b) plays a small role in explaining mobility. Thus, we can write the probability of accepting a job offer as follows:

$$g(\cdot) = g(p, c, r) \tag{3}$$

where the probability of accepting a new academic position depends on personal characteristics (p), mobility costs (c), and the research and reputation effect (r).

Among personal characteristics (p), a key determinant of the probability of accepting a job offer is the academic position of the researcher (pt). Non-tenured researchers are more likely than tenured university staff to accept an offer since they have a non-zero probability of non-renewal of contract (all non-tenured positions are based on "soft" money that is time limited). Individual personal characteristics (pf), such as age and gender, can affect the probability of accepting an offer due to family-related considerations which can increase or decrease mobility costs.

The probability of accepting an offer $g(\cdot)$ depends negatively on mobility costs (c). Mobility costs include the direct personal costs of moving to another city or country, and the skills-adjustment costs—particularly important in high-skilled jobs. If the researcher's skills are university specific (i.e. not all the routines of the academic teaching and research work are transferable to the work in the new university), it will be necessary to learn new practices, protocols, and routines, and adjust to different management and administration procedures. This may result in a period of adjustment with lower expected efficiency. Even when these skill adjustments are minor, they can be considered sunk costs and may deter some researchers from moving.[5] This applies especially to mature academic researchers who have invested a lot of time in accumulating the skills and reputation needed to succeed in a specific university environment. Due to learning effects, both the direct and skills adjustment mobility costs are decreasing in the number of times a researcher has moved. Individual personal characteristics (*pf*) affect the assessment of mobility and adjustment costs.

Scientific performance (*sp*) is a specific personal characteristic that directly affects the probability of receiving *f(·)* and indirectly affects acceptance of a job offer *g(·)*. Researchers with a good publications track record will have better career and retention package prospects affecting *g(·)*. However, more productive academic researchers will have a higher chance of receiving a job offer from another university since research performance usually is considered the most important criterion for selection (conditio sine qua non). Scientific productivity can be seen as signaling a high-quality researcher, increasing the probability of receiving an offer *f(.)* and decreasing the probability of accepting an offer *g(·)*.

Finally, according to the discussion in the previous section, the probability of accepting an offer *g(·)* depends also on the researcher's expectation of higher research performance (*r*) achievable in the new job at a higher ranked institution. We can therefore write the mobility model as:

$$M = f(\cdot) \times g(\cdot) = f(sp, s, e) \times g(sp, pt, c(pf), r) \tag{4}$$

2.2.2 Productivity model

We now turn to the impact of mobility on scientific productivity (*sp*). The researcher's post-mobility productivity is affected by the reasons for the move. For example, a researcher moves to a new job if the value V_{t+1} of her utility function is higher than the value V_t before the move at time *t*. This may be due to the traditional job search-related factors discussed above, and/or because of an expected better research and reputation environment (*r*). Only if the job change is driven by research- and reputation-related motives can we expect a positive impact on performance. Hence, not all types of job mobility are associated with increased research productivity.

Accordingly, scientific productivity is affected by mobility events determined by research and reputation motives *M* (*r*), individual academic characteristics such as career rank *pt*, individual personal characteristics such as gender *pf*, and institution-, field-, country-, and time-specific environmental characteristics *h* (e.g. there is a greater tendency to publish and cite more in medicine than in economics). We can therefore write the productivity model as:

$$sp = f(M(r), pt, pf, h) \tag{5}$$

Mobility is expected to be associated with an increase in productivity due to its effects on matching and networking. In terms of matching, the model predicts that researchers with high potential productivity unexploited in a lower quality department, can expect to increase their performance in a higher ranked institution because there will be more capital available for research, crucial in the natural and biomedical sciences where laboratory costs (equipment and human capital) are extremely high (Stephan, 2012).[6] In terms of networking, interpreted as better human (more diverse learning opportunities) and social (better network connections) capital, the model predicts that a move to a better department means a move to a higher quality research group with positive peer and network effects which increase the researcher's performance. Research group composition and local peer effects have been identified as important predictors of individual performance (Ham and Weinberg, 2008), and researchers are more productive if they collocate with productive scientists. However, Kim et al. (2009) find that peer-effects have diminished since the 1990s, perhaps due to improved communication technology (see also Ding et al., 2010). Working in a department with high-quality peers enhances performance not only through direct interactions but also through privileged access to their social networks. In addition, mobile researchers continue to benefit from their existing networks, which they bring to the new environment (Azoulay et al., 2010; Waldinger, 2012), thereby creating new extended networks with the potential for new knowledge combinations. It is very difficult to disentangle the matching effect from the social/ human capital model since, in high-reputation departments, both are present (funding for good labs, and high ranked

5 A related interpretation of mobility costs can be found in Shaw (1987).

6 Positive social effects results also from the mobility to lower ranked institutions which frees up space in higher ranked institutions for hiring higher performing scientists.

peers who enable access to better quality social networks and more learning). Also, reputable researchers tend to concentrate in high-ranked departments (Oyer, 2007) because they are the source of the ranking and, due to competitive allocation of resources, these departments receive the most funding.

Within this framework, we hypothesize that only a move to a higher quality/reputation institution will be associated with a medium-term increase in research productivity; after an initial period when adjustment costs may constrain researchers' productivity, we can expect increased research performance. On the basis that scientific production is strongly affected by the phenomena of cumulativeness and self-reinforcement (Dasgupta and David, 1994), we would expect that improved medium-term productivity will be persistent and, thus, will affect the long-term performance of researchers.

H1: Academic job mobility to a higher ranked institution is associated with an increase in research productivity.

Conversely, mobility to an institution of the same or lower quality/reputation will be associated with short-term lower productivity due to adjustment costs. These will be only slightly mitigated and at best stabilize at pre-mobility levels (for same rank changes) or at lower performance levels in the medium to long term, due to research resource constraints (such as financial and human support resources) and reputation, assuming the move involves a similar work profile (e.g. similar teaching and administration loads).[7]

H2: Academic job mobility to a lower ranked institution is associated with a decrease in scientific productivity.

In the basic job search model, the difference $V_{t+1} - V_t$ should be higher than the mobility costs (c) for a job change to happen. Mobility costs are assumed to be immediate. However, mobility can be associated with significant deferred adjustment costs which can have a negative impact on post-mobility productivity because the researcher will have less time to spend on research activities due to the need to devote time to learning to perform tasks that were accomplished more efficiently in the previous job because of the scientist's familiarity with its practices, protocols, and routines (Shaw, 1987; van Heeringen and Dijkwel, 1987; Groysberg, 2008). Following a job change in laboratory-based work, the researcher can show decreased productivity associated with the setting up of a new laboratory. The extent of this reduced performance will depend on the relevance of the adjustment costs, which, in turn, will depend on the learning required to adjust to the new job.

H3: Academic job mobility is associated with a short-term decrease in research productivity due to adjustment costs.

3. Empirical analysis

The empirical study is based on a sample of 171 research active academics working at 53 different UK universities in 2005, in four scientific fields: chemistry, physics, computer science, and mechanical, aeronautical, and manufacturing engineering.[8] CVs were collected for all 171 researchers and information on academic performance was complemented with information from the Web of Science (WoS). We coded career information taken from CVs to construct comprehensive profiles for all 171 researchers, spanning their careers from PhD award to 2005, resulting in a panel for the period 1957–2005. Researchers' CVs include unique information on career paths and the timing and nature of job transitions allowing us to identify the exact year of mobility. Using data collected from CVs we were also able to improve the accuracy of the publication data collected from WoS since we were able to avoid mismatches arising from similar names and changes in researchers' institutional affiliations.

7 Relaxing this assumption would mean considering either the case where the work load diminishes (a move to a department with lower reputation, but which involves less teaching because the researcher is considered a star) resulting in a positive impact on scientific productivity, or the case of a move to a more teaching-intensive institution (e.g. because it was impossible to get tenure/permanent contract in a top department), resulting in a decrease in productivity. A typical example of the first situation is a move to a lower-ranked institution associated with promotion to full professor.

8 The sample is based on a 2004 survey of academic researchers that were awarded a grant from the Engineering and Physical Sciences Research Council (EPSRC) at least once between 1999 and 2003, and who therefore can be considered research active. In a second survey round the subsample of 666 academics in the four scientific fields of interest were asked to submit CVs and 171 replies were obtained. See Crespi et al. (2011) for a detailed description of the database and a response rate analysis.

In our analysis we focus on inter-institutional "real" labor mobility (Crespi et al., 2007), which implies a change in job position from one institution to another. Changes in job position within the same institution are not considered (e.g. a move to a different department in the same university). We also consider only changes that occur after the first "tenure-track" or permanent position in academia or first full-time position in industry, after award of the PhD degree.[9] We do not include in this analysis postdoctoral mobility as postdoctoral mobility and job mobility show very different patterns (Zubieta, 2009), due to the temporary characteristic of postdoc and other short-term research fellowships.

In the UK, the minimum tenure-track positions in academia are lecturer, followed by "senior lecturer," "reader," and "professor." Since the early 1990s, parallel to the traditional teaching and research academic career ladder, there has been the development of a research-only career within the university system financed by soft money with a large increase in short-term contracts at research fellow level. Most often, there are three types of research position: research fellow, senior research fellow, and research professor. There is quite some variety in the way in which this research positions are regulated by the different universities and some of them can be more short term than others. We considered research fellow positions a tenure-track equivalent to lecturer only if they continue for at least 5 years, indicating a long-term relationship with the university, equivalent to a probation period. Academics in the UK are usually hired on permanent contracts, which, in the case of lecturer appointments or research fellowships, are subject to a 3-year probation period. Thus, mobility in our sample is likely to be voluntary, that is, where researchers leave a permanent position for reasons other than termination of contract.

The academic market in the UK differs from that in the rest of Europe. It is characterized by its internationality—it attracts academics from across the world, and by the competition amongst its universities for the most promising scholars (Ziman, 1991; BIS, 2011). Further, the three-step promotion system and race for positions at the most prestigious institutions (Hoare, 1994) make the UK system more competitive than other academic systems in Europe. There is no obligation to move after PhD completion; however, mobility barriers are very low and mobility is usually rewarded, making the UK academic labor market very fluid.

Our sample consists of researchers aged 29–77 years, who were active in 2005. The mean age of the sample is 49 in 2005. The first researcher joins our sample in 1957 and the last in 2003. Accordingly, the career years recorded in our sample range from 3 to 49, with an average observation period of 20 years. In our sample of 171 UK academics, 145 (85%) started their careers as lecturer or research fellow, 22 researchers (13%) took up a first position in industry, and 2 researchers started in senior academic positions. For two researchers, first position was not evident from their CVs. The mean starting age is 28.6 with a minimum of 22 years and a maximum of 38 years.[10] The mean PhD age is slightly lower at 27.2 years. Among the researchers, 45.2% took up their first position immediately after PhD award and 48.8% embarked on postdoctoral research; 6% of the researchers in our sample started their work careers during or before studying for their PhD degree; 109 researchers (64%) changed jobs at least once during their career. In total, we have 159 job changes, with 31 academics changing positions twice during their career, 8 academics changing three times, and 1 researcher moving four times. The mean number of years in one job is 10.

While we consider only researchers that worked at UK universities in 2005, this includes researchers from outside the UK and those with a background in industry. Along their careers, 28 researchers changed jobs between industry and academia, and 20 researchers moved internationally. Fifty researchers (29%) were born and raised outside the UK, primarily in Europe (33 researchers). Researchers often move away from their place of birth to take up a first permanent post: first permanent position is outside county of birth for 52 researchers, including 11 UK-born researchers that take up a permanent position in another country. However, the majority of researchers find a position in their country of birth, as indicated by the median distance between first permanent job and place of birth (176 miles).

Between 1982 and 2005, the academics in our sample produced an average 4.45 publications per year. Eighty-eight researchers (59%) published their first article during their PhD study or a postdoctoral appointment, but before taking up their first tenured employment. The average number of publications per researcher per year increased from an average of 4.08 in 1982 to 5.05 in 2005 with a similar increase in publication quality. Quality is measured as

9 In only 12 cases was the first position taken up before completion of the PhD. This can be due to appointment to academic staff before degree completion or to an initial career in industry followed by a later return to academia.

10 Researchers joining the sample at an older age may have pre-PhD experience in academia or industry; however, this is not recorded in our data.

number of WoS citations to a publication in the first 5 years. For quality-adjusted publications, numbers increased from 46 in 1982 to 74 in 2005; this could be due to life cycle, year or mobility effects which this article attempts to measure.

3.1 Mobility and reputation

In the theoretical part of this article, we stressed the importance of research and reputational factors for explaining the academic labor market. Access to resources and an improved research environment are incentives to move and are fundamental when analyzing the impact of mobility on scientific productivity. In the period analyzed in the article, wages paid a less important role in the UK academic labor market in particular because of the high level of standardization in UK academic salary scales (Deloitte, 2012). We assume that mobility is driven by reputation factors and, therefore, identify job changes to either higher or lower quality/reputation institutions.

To measure university prestige, we build an original indicator of the university's disciplinary research ranking, based on publication productivity and quality. We use WoS publication data on UK Higher Education Institutions (HEI) compiled by *Thomson Evidence*, for two main subject categories—natural sciences and engineering sciences—for the years 1982 to 2005.[11] Our data include information on researchers in chemistry, physics, computer science, and mechanical engineering. The first two belong to the natural sciences and second two to the engineering discipline. We calculate our research ranking indicator as percentile ranks (PR) based on the underlying distribution of impact weighted productivity (IWP) of a given department per year, normalized linearly. Thus, we measure the contribution of the particular HEI to the production of the UK sector relative to the highest contributor.[12]

This measure of research reputation for a 23-year panel can be constructed only for UK universities. Thus, our econometric analysis can only study academic job changes between 1982 and 2005; it excludes mobility from companies (28 researchers), leaving a sample of 124 researchers including international mobility, and 108 researchers in the case of within UK mobility.[13]

Researchers in this reduced sample worked at 52 different UK institutions between 1982 and 2005, and 58 moves between UK universities involved 48 researchers. According to the *PR* indicator, among the 52 UK universities in the sample, 47 are in the top 50% and 17 are in the top 10% in the engineering and science disciplines.

Upward mobility is defined as a move to a department ranked at least 5 percentile points higher than the previous department in the year preceding the move (before the focal academic joined the new department); downward mobility is defined as a move to a department ranked at least 5 percentile points lower than the previous department. In our sample, between 1982 and 2005, 21 academics were involved in 22 moves to more prestigious institutions, and 19 researchers were involved in 19 moves to less prestigious institutions.[14]

Figure 1 shows the mean number of publications for the 5 years prior to and following the move. We plot the graph for: the nonmobile sample, for all moves between UK universities, for upward mobility, and for downward mobility. We assume a 1-year lag between the research and its publication. Thus, articles published in the year of the move (year zero) refer to research undertaken at the previous institutions. The disruption caused by the mobility event will result in the publication pipeline drying up and decreased publication numbers in year 1. Figure 1 confirms the 1-year lag between move and publication output. This may reflect mobility and adjustment costs which likely result in a decrease in research efficiency in year t. However, the number of publications increases from year 2 on. In the case of downward mobility, publication rates do not improve, they only return to pre-mobility levels. On average, a mobile researcher making a downward move performs worse than a nonmobile researcher. An upwardly mobile researcher produces a higher number of publications even in the years before the move than a downward moving or nonmobile researcher. The mean number of publications in the case of an upward move increases further, from year 2 after the move. Hence, academics moving to higher-quality institutions are already performing above the average

11 *Thomson Evidence* cleans UK address information found in WoS (taking account of university mergers) and completes missing records.

12 See Appendix A for the technical details of the ranking indicator. This is not expected to be significantly affected by individual research movements due to the low proportion of changes in the production of mobile researchers compared with total university and department production.

13 We also had to exclude 19 researchers because of incomplete information on the year of promotion.

14 We observed 15 lateral moves, i.e. moves between universities of equal or similar ranking. They are not analyzed separately here.

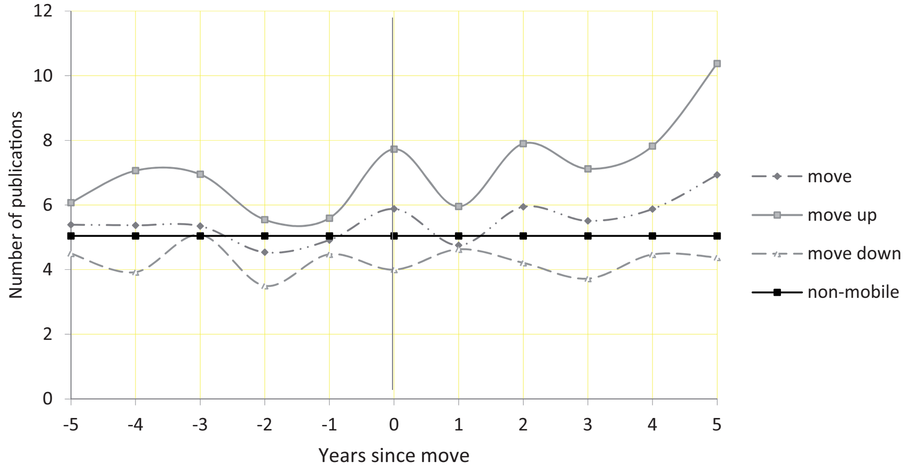

Figure 1. The average number of publications per academic per year in the 5 years prior and after the move.

Note: "non-mobile" denotes the sample average for nonmobile academics. The time line does not apply

before the move, while academics moving to less prestigious universities are those showing below average performance. The difference between the two groups increases further in the years following the move. These results are consistent with the positive effect of job changes into a better department on productivity found by Allison and Long (1990). However, in contrast to their results, Figure 1 shows that the upward moving group starts out with higher productivity than the downward moving group.

3.2 Econometric specification

We estimate count data models since numbers of publications and citations are necessarily positive values. The data are characterized by over dispersion so we employ pooled negative binomial models that take the form:

$$E(sp'_{it}|M_{it}, X_{it}, c_i) = exp\{\beta_1 M_{it} + \beta_2 X_{it} + c_i + \tau_t + \upsilon_{it}\} \tag{6}$$

where sp'_{it} is the count variable representing scientific productivity (*sp*) as either the publication count (Pub_{it}) or the number of citations per publication per year (Cit_{it}) of researcher *i* in year *t*. M_{it} is the mobility measure, X_{it} is a set of explanatory variables including personal and academic characteristics (*pf, pt*) and institutional effects (*h*). c_i is an individual time-invariant unobserved effect, including ability and attitude, τ_t is the time fixed effect and υ_{it} other time-variant unobserved effects.

To measure the performance difference between the pre- and the post-mobility periods, we assume first a lasting career effect of mobility on publication outcomes, and record mobility as a one-time shift by defining $PostMob_{it} = 1$ for all the years following the first move (or the first upward/downward move). Since the effect of mobility may vary, and different short- and long-term effects could be envisaged, we introduce an indicator variable, Mob_{it}, which takes the value 1 in the year of the move, and include its lags in the regression. We consider lags of 3 years after job transition to investigate the effect of short-term post-mobility research performance.

The advantage of estimating pooled models is that they relax the strict exogeneity assumption of the fixed effects model. However, pooled models do not control for unobserved individual heterogeneity (c_i). In our case, these unobserved effects might be the individual researcher's specific skills which are positively correlated with the right-hand-side variables such as mobility, leading to a potential endogeneity problem. In the presence of unobserved individual heterogeneity (c_i), the estimated coefficient of the mobility variables will be upward biased. This problem can be addressed if pre-sample information on the dependent variable is available. Specifically, Blundell et al. (1995, 2002) suggest a solution which controls for individual heterogeneity (c_i) by specifying the academic's average productivity before entering the sample, that is, by using pre-sample information on publications and citations. The pre-sample mean of the dependent variable is a consistent estimator of the unobserved individual effect (Blundell et al., 1995, 2002) if it mostly corresponds to the academic's intrinsic ability and motivation, both factors that are not directly observable, but which may affect scientific productivity. Blundell et al. (2002) use Monte Carlo simulations to show that the estimator remains consistent in the presence of unobserved heterogeneity and predetermined regressors—the case in our estimation. They show also that the efficiency of the estimator increases with longer pre-sample observation periods. We measure the average number of publications (or citations) published since the start of the PhD and before the academic enters the sample (before appointment to her first position or before 1982), resulting in pre-sample observation periods of at least 3 and up to 21 years with a mean of 4.6 years (median of 4 years).

Theory suggests further that research activity is subject to dynamic feedback (Dasgupta and David, 1994), that is, heterogeneous dynamic effects, because each researcher's performance is driven by cumulative unobserved factors (υ_{it}), such as learning, family, and health, which are not controlled for through fixed effects. Blundell et al. (1995, 2002), therefore, argue that it is important to consider continuous sample-period dynamics when modeling research outcomes. This knowledge stock changes over time and while it increases with experience as a by-product of research, it decreases at a rate of δ as the quality of this knowledge decreases over time. Thus, to proxy for dynamic feedback within the sample period, we calculate the depreciated stock of publications (or citations) published during the observation period. We assume that knowledge depreciates at a constant rate of 10%[15] and the sample period feedback measure is hence defined as:

$$sp'stock_{it} = sp'_{it} - 1 + (1 - \delta)sp'stock_{it-1} \tag{7}$$

The pre-sample value and the stock variable are included in our baseline estimations resulting in a linear feedback model. This dual approach helps to address the problem of endogeneity that arises from correlated individual effects and through feedback from the dependent variable.

Still, the problem of reverse causality of our mobility variables could persist because predicted research performance could be related to both, the decision to be mobile and to past levels of productivity. Some papers address the endogeneity arising from reverse causality between performance and mobility, by employing natural experiments and quasi-randomized assignment (Borjas and Doran, 2012; Moser et al., 2014). However, these are rare events and, therefore, less relevant when looking for evidence to support current policies. Since mobility cannot be randomized, we adopt an IV approach (cf. Wooldridge, 2002a).[16] Finding plausible instruments is thus difficult, especially in the case of mobility and productivity, where one researcher's instrument might be another researcher's hypothesized cause of publication performance.[17] We use two instruments to adjust for a researcher's propensity to be mobile: (i) the time-invariant distance from place of birth and (ii) the time-variant performance mismatch between the researcher and her department.

Distance from birth place or home has been found to be an important factor in motivating mobility. Dahl and Sorenson (2010) showed for a sample of Danish scientists and engineers that the highly skilled also value proximity to family and friends and are willing to forgo a part of their incomes to live closer to home. Franzoni et al. (2012) confirm that family ties are an important motivation for academics to return to their home country. Researchers living further away from their home town or country are thus hypothesized to be more likely to move since such a move will incur lower social costs. We measure distance between birth place and location of first permanent academic appointment. Researchers with a history of mobility benefit less from social ties developed at a younger age which are considered to be the most persistent. Also, experience of pre-job mobility equips the researcher with some mobility skills that reduce the cost of subsequent mobility events. The instrument, distance from home, is measured as the distance between the first permanent position and the researcher's place of birth.[18] The distance is measured in miles using Google Maps. For distances of more than 1000 miles, we calculate flight distance using Air Miles Calculator. Due to the skewedness of the variable, we use the log of the variable plus 1 to normalize the distribution. In our reduced regression sample, for those researchers born in the UK and taking up a first position in a UK university, the average distance to place of birth is 152 miles. When we include researchers from abroad and those that move internationally, the average distance increases to 1105 miles (median is 219 miles).

15 Depreciation rates of 15% or 30% return similar results.

16 Another approach to address endogeneity concerns in this setting are matching techniques based on treatment effects (cf. Wooldridge, 2002a), but due to the small number of individuals in our sample matching was not an adequate technique.

17 See Fernandez-Zubieta et al. (2015b) for a discussion of alternative instrumental variables to study academic mobility.

18 For 13 researchers we measured distance from city of high school education.

The intuition for the performance mismatch instrument is based on the idea that rising star scientists might have incentives to leave departments that are in a relative productivity decline. A scientist with increasing productivity located in a department that overall is experiencing a decrease in performance not only will have high incentives to move out, but will also have high opportunities. The instrument is based on department growth in percentile rank (GPR), which allows us to distinguish between rising and declining departments in terms of productivity. GPR is based on the subject and university-specific PR described in Appendix A and the relative change in individual research performance, measured as the percentage change in quality-weighted productivity (GIP). The instrument varies between 0 and infinite. For all individual performance changes, the instrument is zero if the department has increased its PR over the past 5 years (GPR > 0). If the performance of the department is increasing, the researcher does not have much of an incentive to move out. Instead, being in a decreasing performance department creates incentives for the mobility of the researcher, especially for the ones that manage to improve their research performance. If both the performance of the department and the researcher are decreasing (GPR < 0; GIP < 0, GPR × GIP > 0), then the instrument is equal to the absolute change in GPR. If the performance of the department is decreasing (GPR < 0) and the focal academic has been able to increase her own quality-weighted number of publications during the previous 5 years (GIP > 0, GPR × GIP < 0), then we add the relative personal increase, to the absolute change of the negatively performing department. This is the perfect mismatch case, in which the changes in performance are in opposite directions and the propensity of moving out of the department is highest and depends on the sum of the changes. The instrument built in this way provides a time-variant measure for the propensity to be mobile.[19] For academics at UK universities, we find a negative department trend for 27% of observations. For half of these declining department observations, the focal academic increases his or her own performance during the same observation period.

3.3 Variables

Our primary objective is to measure the effect of job mobility on research productivity. The main dependent variables in our specifications are the number of publications in year t (PUB_{it}) and the total number of citations received by the researcher's publications in the 5 years after publication ($CIT5YR_{it}$).

The main explanatory variables in the regression refer to the mobility event. To measure the potential performance difference between pre- and post-mobility periods, we introduce two dummies that measure the mobility event: (i) $PostMob_{it}$, which switches from zero to 1 in the year of first mobility, clearly indicating the pre- and post-mobility periods; and (ii) Mob_{it}, which takes the value 1 only in the year of the move, indicating a one-time shock. Since our main focus is on mobility between universities, we run additional models for moves between UK universities ($PostUNIMob_{it}$, $UNIMob_{it}$) that exclude all researchers with international mobility experiences. For both the full and the reduced samples (including and excluding international mobility, respectively) we run an IV model in which the first equation explains job mobility using distance from place of birth (*Dis-Birth*) and performance mismatch (*PerfMismatch*) as instruments.

We argued above that mobility is affected by the reputation of the sending and receiving institutions; therefore, we use additional measures for mobility that consider the nature of transition: (i) *Upward Mobility* ($PostUP_{it}$, UP_{it}) defining a move to a higher ranked university, and (ii) *Downward mobility* ($PostDOWN_{it}$, $DOWN_{it}$) defining a move to a less prestigious university.

As controls we include academic's age (AGE_{it}) to account for potential life-cycle effects (Levin and Stephan, 1991) and gender ($FEMALE_i$). We control also for a researcher's academic rank. The UK university system has some minimum requirements for consideration for promotion. Thus, less senior academics should have a greater incentive to publish, while professors, because of their access to research assistance and funding, may achieve high publication rates. We hence consider three levels of seniority in our analysis: Lecturer or Research Fellow before first promotion ($RANK1_{it-1}$), senior position or rank after first promotion ($RANK2_{it-1}$), and professorship ($RANK3_{it-1}$). We also include an indicator for postdoctoral research experience ($POSTDOC_i$). To account for the researcher's commercial orientation (Crespi et al., 2011) we include patent stock ($PATENT_{it-1}$) which counts the number of patents filed in

19 We considered two stricter definitions of performance mismatch (with consequent lost of observations): (i) assuming a mismatch only for rising researchers in a declining department and (ii) if the researcher declines at a slower rate than the department, obtaining similar econometric results.

previous years. To account for any potential department effects related to access to resources and networks, we include the university's rank in $t-1$ as defined in section 3.1 ($UniRanking_{it-1}$), in the set of regressions that consider only UK institutions. We can also expect a "London" effect due to proximity to funding bodies and networks that might positively affect research output, and include a London dummy ($London_{it-1}$). We include subject dummies to control for discipline effects. A summary of the variables used in the regressions and their descriptive statistics is provided in Table 1.

4. Results

We estimate pooled negative binomial regressions. Standard errors are clustered at the individual level and robust to heteroscedasticity and serial correlation. Table 2 shows the results for all (including international) mobility between universities. Table 3 shows the results for mobility between UK universities (excluding internationally mobile academics).

4.1. Feedback model and IV approach

To address the problem of endogeneity arising from unobserved effects and reverse causality, we use the linear feedback model (Blundell et. al., 2002) by including the pre-sample mean and dynamic feedback measure in our models in Table 2 and Table 3 (Columns 1–4). Both measures are significant and positive in the publication equation, while only the measure for dynamic stock is significant in the citations count equation (Column 3 and 4). The implementation of the "quasi-fixed" effect measured by the pre-period mean of the dependent variables and their moving stock, which accounts for dynamic effects, allows us to proxy for researcher's ability and avoids confusing ex-ante conditions with ex-post events. The feedback model thus reflects the stock of knowledge that is available ex-ante and the effect of mobility should therefore be net of these ex-ante effects.

We also estimate an IV model using distance from place of birth and performance mismatch as instruments. We test for endogeneity and the validity of the IV approach, based on the two-step model described in Wooldridge (2002b). The residuals-based Smith-Blundell test rejects exogeneity of our mobility variable in the publication equation, but not in the citation equation. We further use the Hansen's J statistic to test for the over-identifying restrictions, verifying that our instruments are exogenous. The results of the instrumented model are presented in Columns 7 and 8.[20] Both Tables 2 and 3 present the first stage of our IV estimation (marginal effects in column 6). We find that our instruments have a positive and significant effect on mobility. The results also confirm several of the mobility drivers discussed in Section 2. We find: a negative age effect, the older the researcher the lower the probability of changing job; women have a lower probability of moving; probability of mobility increases with rank, especially from lecturer to senior lecturer; researchers with postdoctoral experience are more likely to be mobile; and researchers working in London have a higher probability of mobility probably due to the lower mobility costs associated with the concentration of universities in London. We found evidence of an important relative opportunity advantage with researchers at more prestigious institutions showing a lower propensity to move. The time fixed effect shows that mobility propensity increased over time up to 1997 and then stabilized. There are some differences between the results in Tables 2 and 3. Table 2 shows a lower propensity to move among women, who likely face higher mobility costs for international mobility. We also find a negative effect for patent stock, which only becomes significant in the case of international mobility.

The results of the two models, the feedback model and the IV model, show that the effect of the post-mobility indicator is the same in sign in both approaches. The coefficients are even larger in the case of the IV model and that the feedback model may provide the more conservative estimates. The results of the IV model thus also confirm the robustness of the results from the feedback model.[21]

20 Results of the IV-Model without mobility lags are presented in Appendix B Table B1.

21 If we estimate the non-IV model without controlling for the two feedback variables (naïve model), the coefficients of the mobility measures increase and become significant, suggesting that the feedback model is able to capture some of the endogeneity inherent in the model (results presented in Appendix B Table B2). This confirms the robustness of the approach.

Table 1. Definition and Summary Statistics of variables used in the regression 1982–2005

Variables	Definition	Full Sample of HE 1850 observations				Reduced Sample of UK-HEI 1579 observations			
		Mean	SD	Min	Max	Mean	SD	Min	Max
Dependent variable									
PUB_{it}	Number of publications in t	5.19	6.80	0.0	97	5.52	7.24	0.0	97
$CIT5YR_{it}$	Number of citations in t to $t+5$ to publications in t	70.78	108.24	0.0	1122	75.37	113.55	0.0	1122
Mobility variable									
$PostMOB_{it}$	Moved at least once between HEI before t	0.33	0.47	0.0	1				
MOB_{it}	Moved between HEI in t	0.04	0.20	0.0	1				
$PostUNIMOB_{it}$	Moved at least once between UK HEI before t					0.27	0.44	0.0	1
$UNIMOB_{it}$	Moved between UK HEI in t					0.03	0.18	0.0	1
$PostUP_{it}$	Moved upward at least once before t					0.10	0.30	0.0	1
UP_{it}	Moved upward in t					0.01	0.11	0.0	1
$PostDOWN_{it}$	Moved downward at least once before t					0.12	0.33	0.0	1
$DOWN_{it}$	Moved downward in t					0.01	0.11	0.0	1
Feedback measures									
Pre-sample $average_i$ (PUB)		0.70	0.67	0.0	3	0.76	0.66	0.0	3
$Stock_{it-1}$ (PUB)		27.65	35.34	0.0	439	29.36	37.49	0.0	439
Pre-sample $average_i$ (CIT)		9.50	14.39	0.0	75	10.22	14.12	0.0	69
$Stock_{it-1}$ (CIT)		358.12	517.91	0.0	5499	376.34	544.55	0.0	5499
Instrument									
Dis-Birth	Log +1 of distance between place of birth and first position	4.99	2.58	0.0	9	5.00	2.31	0.0	9
PerfMismatch	Log +1 of performance mismatch between the researcher and her department	0.10	0.37	0.0	3.90	0.11	0.35	0.0	3.66
Control variables									
AGE_{it}	Age in t	43.46	10.34	25.0	77	43.58	10.46	26.0	77
$FEMALE_i$	Dummy = 1 if female	0.11	0.31	0.0	1	0.10	0.31	0.0	1
$RANK1_{it-1}$	Lecturer or Research Fellow in t	0.33	0.47	0.0	1	0.33	0.47	0.0	1
$RANK2_{it-1}$	Senior position in t	0.33	0.47	0.0	1	0.35	0.48	0.0	1
$RANK3_{it-1}$	Professor in t	0.34	0.47	0.0	1	0.32	0.47	0.0	1
$POSTDOC_i$	Dummy = 1 if postdoc before first position	0.50	0.50	0.0	1	0.53	0.50	0.0	1
$PATENT_{it-1}$	Stock of patents up to t−1	0.95	3.11	0.0	25	1.11	3.34	0.0	25
$UNIRANKING_{it-1}$	Ranking of UK HEI in $t-1$					0.31	0.32	0.0	1
$LONDON_{it-1}$	Dummy = 1 if working in London in $t-1$	0.13	0.33	0.0	1	0.12	0.32	0.0	1
$CHEMISTRY_i$	Chemistry	0.47	0.50	0.0	1	0.51	0.50	0.0	1
$PHYSICS_i$	Physics	0.30	0.46	0.0	1	0.29	0.45	0.0	1
$COMPUTER_i$	Computer Science	0.11	0.32	0.0	1	0.09	0.29	0.0	1
$MECHANICAL_i$	Mechanical Engineering	0.12	0.33	0.0	1	0.11	0.31	0.0	1

Table 2. Effect of overall HE-mobility on publication performance

Model	Non-instrumented with feedback measures (Blundell et al. 2002)				IV 1st stage Coef.	Marginal effects	IV 2nd stage	
Variables	(1) NBREG PUB	(2) NBREG PUB	(3) NBREG CIT5YR	(4) NBREG CIT5YR	(5) LOGIT $PostMob^{it}$	(6) LOGIT $PostMob^{it}$	(7) NBREG-IV PUB	(8) NBREG-IV CIT5YR
Pre-sample Average (PUB/CIT)	0.115**	0.120**	0.005*	0.002				
	(0.054)	(0.056)	(0.003)	(0.003)				
Stock (PUB/CIT)	0.013***	0.013***	0.001***	0.001***				
	(0.002)	(0.002)	(0.000)	(0.000)				
Dis_birth					0.109***	0.018***		
					(0.027)	(0.004)		
PerfMismatch					0.513***	0.083***		
					(0.175)	(0.028)		
$PostMob^{it}$	0.088	0.073	0.105	0.104			0.336	1.364*
	(0.069)	(0.069)	(0.096)	(0.092)			(0.582)	(0.699)
L. Mob^{it}		−0.159		−0.011			−0.137	−0.052
		(0.097)		(0.154)			(0.117)	(0.174)
L2. Mob^{it}		0.009		0.050			0.101	0.231
		(0.089)		(0.124)			(0.117)	(0.210)
L3. Mob^{it}		−0.094		−0.185			−0.017	−0.132
		(0.107)		(0.141)			(0.112)	(0.144)
AGE^{it}	0.039	0.016	0.083*	0.069	0.140**	−0.010***	0.040	−0.007
	(0.029)	(0.032)	(0.045)	(0.053)	(0.062)	(0.002)	(0.055)	(0.074)
AGE^{it} 2	−0.000	−0.000	−0.001**	−0.001	−0.002***		−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)		(0.001)	(0.001)
$FEMALE^{i}$	0.146	0.004	0.067	−0.122	−0.534**	−0.087**	0.326	0.119
	(0.135)	(0.096)	(0.135)	(0.134)	(0.228)	(0.037)	(0.295)	(0.280)
Reference: $RANK1^{it-1}$								
$RANK2^{it-1}$	0.089	0.078	−0.086	−0.061	1.227***	0.179***	0.183	−0.034
	(0.076)	(0.073)	(0.131)	(0.130)	(0.200)	(0.027)	(0.209)	(0.227)
$RANK3^{it-1}$	0.070	0.062	−0.101	−0.083	1.935***	0.302***	0.258	−0.205
	(0.107)	(0.106)	(0.163)	(0.163)	(0.234)	(0.032)	(0.258)	(0.304)
$POSTDOC^{i}$	−0.133	−0.071	−0.017	0.059	0.421***	0.068***	−0.345**	−0.375**
	(0.090)	(0.082)	(0.110)	(0.109)	(0.133)	(0.021)	(0.168)	(0.177)
$PATENT^{it-1}$	−0.003	−0.001	−0.002	−0.002	−0.063**	−0.010**	0.004	0.005
	(0.007)	(0.007)	(0.010)	(0.009)	(0.027)	(0.004)	(0.021)	(0.022)
$LONDON^{it-1}$	−0.112	−0.062	−0.221	−0.211	1.852***	0.301***	−0.057	−0.511*
	(0.117)	(0.116)	(0.164)	(0.160)	(0.216)	(0.033)	(0.226)	(0.291)
Reference: $CHEMISTRY^{i}$								
$PHYSICS^{i}$	−0.075	−0.083	−0.127	−0.140	−0.432***	−0.070***	−0.338**	−0.452**
	(0.082)	(0.077)	(0.119)	(0.123)	(0.147)	(0.024)	(0.163)	(0.207)
$COMPUT\ ER^{i}$	−0.953***	−0.839***	−1.742***	−1.732***	−0.136	−0.023	−1.614***	−2.858***
	(0.154)	(0.138)	(0.233)	(0.235)	(0.221)	(0.037)	(0.202)	(0.267)
$MECHANICAL^{i}$	−0.601***	−0.556***	−1.240***	−1.247***	−0.391**	−0.064**	−1.136***	−2.005***
	(0.172)	(0.161)	(0.221)	(0.210)	(0.192)	(0.031)	(0.218)	(0.250)
Constant	0.642	1.173	2.258**	2.556**	−3.411**		0.548	3.524**
	(0.670)	(0.750)	(0.999)	(1.208)	(1.403)		(1.171)	(1.534)
lnalpha	−1.208***	−1.366***	0.392***	0.305***			−0.710***	0.452***
log Likelihood	−4436.187	−4062.195	−8847.143	−8113.580	−854.376		−4310.106	−8158.740
Observations	1850	1673	1850	1673	1747		1652	1652

continued

Table 2. (Continued)

Model	Non-instrumented with feedback measures (Blundell et al. 2002)				IV 1st stage Coef.	Marginal effects	IV 2nd stage	
Variables	(1) NBREG PUB	(2) NBREG PUB	(3) NBREG CIT5YR	(4) NBREG CIT5YR	(5) LOGIT *PostMob*^{it}	(6) LOGIT *PostMob*^{it}	(7) NBREG-IV PUB	(8) NBREG-IV CIT5YR
Clusters	124	122	124	122			122	122
Smith-Blundell Test of Exogeneity (*P*-value)							0.077	0.881
Hansen's J statistic (*P*-value)							0.133	0.466
Wald-test of significance of excluded instruments					23.41***			
McFadden's R2					0.240			

Robust clustered standard errors in parentheses; Year fixed effects in all models; $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.
Feedback model and IV model.

4.2. Main results

In Table 2, which shows the results for all (including international) mobility between higher education institutions, the number of observations in Column 1 is 1850 which reduces to 1673 in Column 2 due to longer lags that require a minimum of four observation years, i.e. consider only academics whose careers began before 2003.

Column 1 shows publication performance changes after the mobility event. The mobility variable is positive, but insignificant, indicating that academics do not perform significantly better after mobility.[22] Column 2, which presents the yearly effects of the mobility shock, shows some evidence of a short-term negative effect, albeit insignificant. The results are similar for citation-weighted output (Columns 3 and 4).

The results of the instrumented model are presented in Columns 7 and 8. The results show that also for the instrumented post-mobility indicator we find no significant effect on academic performance in terms of publications. The effect on quality-weighted publications is positive and significant.

We can conclude that the results for the general mobility measures give weak support to our third hypothesis of an initial negative effect on research performance. We can observe negative signs in the first few years following mobility, but these effects remain insignificant. We also find no strong support for mobility having a positive impact on scientific performance.

To introduce our ranking measure *PR* which takes account of the quality of the university department, we consider only mobility between UK universities (Table 3). We include researchers who were born abroad but have moved only within the UK, but exclude all researchers that moved internationally as it was not possible to produce a 23-year field-specific ranking that includes non-UK organizations. The number of observations reduces to 1579 in Column 1 and 1424 in Column 2.

Column 1 shows how publication performance changes after the mobility event. The mobility variable is positive, indicating that mobile academics perform better than nonmobile academics after mobility, but that the effect is insignificant. In Column 2, which looks at the effects of the mobility shock, the post-mobility variable remains insignificant. As in Table 2, there are indications of a weakly significant negative short-term effect of mobility. The results are similar but not significant for citation output (Columns 3 and 4). These findings are confirmed in the IV model (Columns 7 and 8). We observe a positive, albeit insignificant effect of mobility and a negative short-term effect.

22 We also analyzed the difference in research performance between mobile and nonmobile researchers to investigate whether mobile researchers have a performance premium compared to nonmobile researchers, along the whole of their career. The mobility dummy is positive, but insignificant, indicating that mobile academics do not perform better relative to the group of nonmobile researchers. If we exclude post-mobility observations of mobile academics, an estimator that corresponds to a pre-mobility indicator and shows whether researchers were more productive before the move, we still find a positive, but insignificant effect.

Table 3. Effect of mobility between UK-HEI on publication performance

MODEL	Non-instrumented with feedback measures (Blundell et al. 2002)				IV 1st stage Coef.	Marginal effects	IV 2nd stage	
Variables	(1) NBREG PUB	(2) NBREG PUB	(3) NBREG CIT5YR	(4) NBREG CIT5YR	(5) LOGIT $PostMob^{it}$	(6) LOGIT $PostMob^{it}$	(7) NBREG-IV PUB	(8) NBREG-IV CIT5YR
Pre-sample Average (PUB/CIT)	0.109*	0.117*	0.004	0.002				
	(0.061)	(0.063)	(0.003)	(0.003)				
Stock (PUB/CIT)	0.013***	0.013***	0.001***	0.001***				
	(0.002)	(0.002)	(0.000)	(0.000)				
Dis_birth					0.114***	0.017***		
					(0.035)	(0.005)		
PerfMismatch					0.433**	0.065**		
					(0.198)	(0.030)		
$PostMob^{it}$	0.114	0.130	0.126	0.133			0.800	1.107
	(0.086)	(0.087)	(0.111)	(0.109)			(0.623)	(0.772)
L. Mob^{it}		−0.220*		0.012			−0.285**	−0.156
		(0.115)		(0.196)			(0.135)	(0.203)
L2. Mob^{it}		−0.075		−0.012			−0.021	0.020
		(0.093)		(0.138)			(0.139)	(0.177)
L3. Mob^{it}		−0.146		−0.155			−0.109	−0.196
		(0.122)		(0.167)			(0.128)	(0.181)
AGE^{it}	0.036	0.006	0.089*	0.080	−0.013	−0.012***	0.038	0.024
	(0.031)	(0.033)	(0.047)	(0.054)	(0.080)	(0.002)	(0.058)	(0.075)
AGE^{it} 2	−0.000	−0.000	−0.001**	−0.001*	−0.001		−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)		(0.001)	(0.001)
$FEMALE^{i}$	0.192	0.020	0.150	−0.092	0.184	0.028	0.412	0.206
	(0.157)	(0.113)	(0.171)	(0.166)	(0.228)	(0.034)	(0.323)	(0.309)
Reference: $RANK1^{it-1}$								
$RANK2^{it-1}$	0.106	0.094	−0.036	−0.020	1.620***	0.208***	0.121	0.068
	(0.084)	(0.081)	(0.142)	(0.143)	(0.237)	(0.026)	(0.238)	(0.277)
$RANK3^{it-1}$	0.144	0.136	0.002	−0.009	2.043***	0.278***	0.295	0.080
	(0.130)	(0.125)	(0.184)	(0.187)	(0.290)	(0.033)	(0.276)	(0.338)
$POSTDOC^{i}$	−0.186*	−0.108	−0.017	0.092	0.407***	0.061***	−0.491***	−0.346*
	(0.103)	(0.092)	(0.125)	(0.124)	(0.153)	(0.023)	(0.180)	(0.202)
$PATENT^{it-1}$	−0.003	−0.000	−0.004	−0.004	−0.031	−0.005	0.005	−0.008
	(0.008)	(0.007)	(0.013)	(0.011)	(0.024)	(0.004)	(0.021)	(0.023)
$UniRanking^{it-1}$	0.053	0.079	0.311**	0.287*	−0.725***	−0.109***	0.155	0.450*
	(0.107)	(0.113)	(0.144)	(0.158)	(0.242)	(0.036)	(0.200)	(0.254)
$LONDON^{it-1}$	−0.074	−0.057	−0.193	−0.225	1.158***	0.174***	0.030	−0.167
	(0.141)	(0.133)	(0.199)	(0.189)	(0.223)	(0.033)	(0.225)	(0.288)
Reference: $CHEMISTRY^{i}$								
$PHYSICS^{i}$	−0.063	−0.074	−0.157	−0.173	−0.581***	−0.088***	−0.262	−0.475**
	(0.088)	(0.084)	(0.133)	(0.139)	(0.165)	(0.024)	(0.176)	(0.242)
$COMPUTER^{i}$	−1.133***	−0.961***	−1.860***	−1.797***	−1.044***	−0.147***	−1.746**	−2.786***
	(0.197)	(0.179)	(0.292)	(0.298)	(0.272)	(0.033)	* (0.262)	(0.381)
$MECHANICAL^{i}$	−0.640***	−0.582***	−1.320***	−1.331***	−0.292	−0.046	−1.153***	−2.090***
	(0.215)	(0.202)	(0.255)	(0.235)	(0.231)	(0.036)	(0.273)	(0.292)
Constant	0.798	1.453*	2.086**	2.235*	−0.035		0.502	2.982*
	(0.711)	(0.768)	(1.053)	(1.239)	(1.776)		(1.299)	(1.635)
lnalpha	−1.174***	−1.337***	0.362***	0.273***			−0.713***	0.432***

continued

Table 3. (Continued)

MODEL	Non-instrumented with feedback measures (Blundell et al. 2002)				IV 1st stage Coef.	Marginal effects	IV 2nd stage	
Variables	(1) NBREG PUB	(2) NBREG PUB	(3) NBREG CIT5YR	(4) NBREG CIT5YR	(5) LOGIT *PostMob*^{it}	(6) LOGIT *PostMob*^{it}	(7) NBREG-IV PUB	(8) NBREG-IV CIT5YR
log Likelihood	−3855.741	−3523.254	−7651.487	−6999.140	−680.958		−3726.888	−7041.415
Observations	1579	1424	1579	1424	1485		1405	1405
Clusters	108	106	108	106			106	106
Smith-Blundell Test of Exogeneity (*P*-value)							0.066	0.174
Hansen's J statistic (*P*-value)							0.165	0.139
Wald-test of significance of Instrument					17.55***			
McFadden's R2					0.223			

Robust clustered standard errors in parentheses; Year fixed effects in all models; ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$
Feedback model and IV model.

Overall these results show that mobile academics do not outperform nonmobile academics, and provide weak support for our hypothesis of an initial negative effect following mobility.

The coefficients for nonmobility control variables vary slightly across the different mobility measures and lags. We report their results from Table 3, in which we control also for university ranking. Age is not significantly correlated with publications, but has an inverted U-shape effect on the quality-adjusted number of publications. Thus, while the number of publications does not change significantly over the life cycle, the quality of publications increases for the first few years of the career and then declines from around the age of 40. We do not find a significant gender effect, which is in line with Crespi et al. (2011) which uses the same sample of researchers. We also do not find an effect of academic rank. Senior academic staff are not expected to publish more than researchers in the category *RANK 1*. The patent stock is negative but insignificant in all estimations confirming Crespi et al. (2011).

We further find that a postdoctoral appointment, or other temporary research contract following the PhD, does not improve future publication numbers or citation counts. Instead, we observe a negative effect that is significant for publication numbers in the feedback model and for publications and citations in the IV models. This negative effect may be due in part to job insecurity and fragmented career path associated with postdoctoral appointments and temporary contracts (Stephan, 2012). This negative effect seems to persist also in later career stages.

University ranking has no significant effect on publication numbers. However, we find a strong positive sign for the quality-adjusted measure. Thus, researchers at the most prestigious institutions may not produce more, but may produce publications that are of better quality and achieve more visibility than those produced by their peers at lower-ranked institutions.

Finally, we find strong differences across disciplines; researchers in chemistry and physics publish significantly more, and are more frequently cited, than colleagues in other fields, with computer sciences researchers producing the least number of publications and receiving the lowest number of citations.

4.3 Mobility and department quality/reputation

In Table 4, the mobility effect is conditioned by the nature of the job transition. We only implement the feedback model since researchers that do not move upwards or downward may still be mobile and the IV model would be misspecified. Also, the above analysis shows that the IV model does not provide significantly different results from the feedback model and we are therefore confident that the feedback model will provide sufficiently consistent estimates.

Table 4 Column 1 measures the effect of upward mobility on publication numbers. The effect is positive and significant at 85% confidence. A detailed look at the short-term effects (Column 2) shows that scientific output decreases in the short term, but that in the long term we can expect a non-negative effect indicated by the strong positive coefficient in *PostUp*.

Table 4. Effect of upward and downward mobility between UK-HEI on publication performance

VARIABLES		(1) UP PUB	(2) UP PUB	(3) UP CIT5YR	(4) UP CIT5YR	(5) DOWN PUB	(6) DOWN PUB	(7) DOWN CIT5YR	(8) DOWN CIT5YR
Pre-sample Average (PUB/CIT)		0.130**	0.135**	0.004*	0.002	0.128**	0.141**	0.005*	0.003
		(0.062)	(0.064)	(0.003)	(0.003)	(0.057)	(0.060)	(0.003)	(0.003)
Stock (PUB/CIT)		0.013***	0.012***	0.001***	0.001***	0.013***	0.012***	0.001***	0.001***
		(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)
$PostUP_{it}$ /	$PostDOWN_{it}$	0.213	0.278**	0.011	0.070	−0.173*	−0.240**	−0.061	−0.215
		(0.135)	(0.127)	(0.172)	(0.161)	(0.096)	(0.097)	(0.144)	(0.149)
L. UP_{it} /	L. $DOWN_{it}$		−0.384**		−0.067		0.270		0.711**
			(0.174)		(0.314)		(0.189)		(0.332)
L2. UP_{it} /	L2. $DOWN_{it}$		−0.246		−0.272		0.116		0.166
			(0.184)		(0.225)		(0.146)		(0.235)
L3. UP_{it} /	L3. $DOWN_{it}$		−0.442**		−0.312		−0.057		0.214
			(0.190)		(0.261)		(0.160)		(0.272)
AGE_{it}		0.036	0.010	0.088*	0.076	0.037	0.013	0.088*	0.088*
		(0.031)	(0.031)	(0.047)	(0.053)	(0.032)	(0.034)	(0.047)	(0.052)
$AGE_{it}2$		−0.001	−0.000	−0.001**	−0.001*	−0.001	−0.000	−0.001**	−0.001**
		(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
$FEMALE_i$		0.218	0.044	0.151	−0.084	0.187	0.010	0.148	−0.091
		(0.155)	(0.113)	(0.168)	(0.164)	(0.154)	(0.113)	(0.166)	(0.164)
Reference: $RANK1_{it-1}$									
$RANK2_{it-1}$		0.121	0.094	−0.001	0.008	0.155*	0.127	0.007	0.019
		(0.082)	(0.079)	(0.136)	(0.141)	(0.086)	(0.084)	(0.141)	(0.145)
$RANK3_{it-1}$		0.186	0.157	0.033	0.019	0.210	0.171	0.042	0.022
		(0.128)	(0.123)	(0.182)	(0.185)	(0.134)	(0.128)	(0.187)	(0.192)
$POSTDOC_i$		−0.190*	−0.111	−0.009	0.100	−0.180*	−0.099	−0.010	0.103
		(0.103)	(0.091)	(0.127)	(0.126)	(0.103)	(0.090)	(0.128)	(0.127)
$PATENT_{it-1}$		−0.001	0.001	−0.004	−0.004	−0.002	0.002	−0.003	−0.002
		(0.009)	(0.008)	(0.013)	(0.012)	(0.010)	(0.009)	(0.014)	(0.012)
$UniRanking_{it-1}$		0.016	0.047	0.296**	0.275*	0.026	0.046	0.288**	0.270*
		(0.097)	(0.104)	(0.144)	(0.159)	(0.109)	(0.115)	(0.147)	(0.163)
$LONDON_{it-1}$		−0.106	−0.086	−0.166	−0.196	−0.035	−0.031	−0.161	−0.231
		(0.138)	(0.130)	(0.197)	(0.186)	(0.141)	(0.133)	(0.193)	(0.184)
Reference: $CHEMISTRY_i$									
$PHYSICS_i$		−0.055	−0.063	−0.163	−0.178	−0.087	−0.100	−0.166	−0.193
		(0.086)	(0.081)	(0.132)	(0.138)	(0.089)	(0.086)	(0.131)	(0.138)
$COMPUTER_i$		−1.123***	−0.952***	−1.893***	−1.827***	−1.162***	−1.009***	−1.903***	−1.877***
		(0.196)	(0.178)	(0.286)	(0.291)	(0.189)	(0.172)	(0.285)	(0.296)
$MECHANICAL_i$		−0.632***	−0.580***	−1.297***	−1.316***	−0.651***	−0.604***	−1.295***	−1.325***
		(0.215)	(0.198)	(0.258)	(0.237)	(0.222)	(0.205)	(0.259)	(0.234)
Constant		0.791	1.375*	2.125**	2.326*	0.791	1.301*	2.129**	2.046*
		(0.707)	(0.734)	(1.053)	(1.217)	(0.734)	(0.787)	(1.056)	(1.200)
lnalpha		−1.181***	−1.355***	0.364***	0.274***	−1.178***	−1.342***	0.363***	0.271***
log Likelihood		−3853.608	−3518.873	−7652.747	−6999.892	−3854.932	−3520.293	−7652.574	−6997.226
Observations		1579	1424	1579	1424	1579	1424	1579	1424
Clusters		108	106	108	106	108	106	108	106

Robust clustered standard errors in parentheses; Year fixed effects in all models; $***P < 0.01$, $**P < 0.05$, $*P < 0.1$.

The estimations for citations confirm the short-term negative effect of upward mobility and the expectation of a non-negative effect in later years, but the coefficients are not significant. The university ranking control variable is positive in Column 3, which considers citation outputs for all researchers. This indicates that while not all researchers that are upward mobile produce better quality research (as indicated by the insignificant coefficient $PostUP_{it}$), researchers in more prestigious departments produce more visible research. Therefore, upward mobile researchers will benefit from this additional prestige effect, potentially outperforming previous peers in their old department (as belonging to a higher ranked department is associated with more citations).

Table 4 Columns 5–8 report the results for downward mobility ($DOWN$). They show that downward mobile researchers have a lower publication productivity than their nonmobile peers, or colleagues who move to higher ranked institutions. This effect persists after isolating the short-term effect in Column 6. The negative signs are confirmed for the quality-adjusted publications measure (Columns 7 and 8).[23] Interestingly, contrary to the case of upward mobility, for downward mobile researchers we find a positive short-term effect of mobility in both the publication and the citation equation. The effect is strongly significant for citation-weighted output, suggesting that academics benefit from a delayed positive effect of their publication pipeline that diminishes quickly. Thus, the results for downward mobility are generally associated with reduced productivity—possibly due to reduced resources. However, for the majority (all but four) of researchers who moved to a lower ranked university, the job change involved a promotion and, thus, potentially more resources. Therefore, the negative effect indicates that lower-ranked institutions do not offer better packages that compensate for loss of institutional prestige and departmental colleagues.

For department quality, we find an additional positive effect for citations. This indicates that researchers moving to a lower-quality institution but joining a department of acceptable high quality may perform better than their counterparts who join a lower-quality department.

Overall, we find no evidence of an overall positive effect of mobility, but the mobility effect is conditioned by the nature of the job transition. The econometric analysis provides some evidence confirming a positive effect of upward mobility (Hypothesis 1) and some evidence of a negative effect of downward mobility (Hypothesis 2). We also found evidence that academic job mobility is most often associated with a short-term decrease in research performance (Hypothesis 3) especially in the case of upward mobile researchers.

5. Discussion and conclusions

This article analyzed the impact of mobility on researchers' productivity. We addressed the relationship by developing a theoretical framework based on a job-matching approach for academics and the idea of performance driven by capital availability and peer effects. We studied job changes and characterized them as upward or downward mobility based on department research and reputation ranking.

The econometric analysis was based on the careers of a sample of 171 UK academic researchers in the period 1982–2005. Based on this sample, which should not be biased towards mobility, we found a high level of job mobility: two-thirds of researchers changed jobs at least once, and one-third was involved in two job moves. In this respect, the UK academic labor market resembles the US system more than other European systems.

First, we analyzed the difference in performance between mobile and nonmobile researchers. In both the feedback model and the IV model, we found a positive albeit insignificant overall effect of mobility, and a negative weakly significant short-term effect. Second, based on a unique robust research ranking system for UK university institutions over the 23-year period of our panel, we studied performance pre- and post-mobility to a better or a worse department than the department of origin. We found that mobility to a higher ranked university has only a weakly positive impact on publications output, but not on citations, while downward mobility tends to decrease the researcher's overall research performance. We found evidence of decreased productivity in the years after a job change—probably or most likely due to adjustment costs. Although upward mobile (though not downward mobile) researchers are more productive than their peers, their scientific performance does not improve in the short term after the mobility event. Finally, downward mobile researchers may benefit from their preexisting publication pipeline when newly

23 For both upward and downward mobility we consider a different quality weighted variable based on the total number of citations received before April 2013 (date of data download) by each year's papers. Thus, we allow for longer (at least 8 years and up to 31 years) time periods of citation accumulation. Results are confirmed with stronger significance for the positive impact of upward mobility.

joining a department, but their performance drops significantly in later years. Thus, hiring of researchers from top departments might be a short-term strategy for lower-ranked departments to improve their visibility with negative long-term productivity pay-offs for the researcher that moves.

Our results point to a complex interaction between job mobility and productivity, which only in certain circumstances might result in a positive impact of the former on the latter. Job mobility is far from being always beneficial for individual researchers, instead, for all mobile researchers, job mobility is associated with a short-term decrease in performance due to adjustment costs, that does not diminish over the longer term for downward mobile researchers. On a side note, we also find some worrying evidence that temporary research positions, which have increased in frequency in the last few years (Stephan, 2012), have a long-term negative effect on research performance.

Turning back to the opening question of our article: should I stay or should I go? Our results show that a researcher should take into consideration the quality of the home and host departments to take a job change decision that will be academically productive. If she wants to increase her performance, she should not move to a lower-quality department even if it offers a higher position or better salary. The results can provide some insights into academic hiring policies. Departments and universities that choose the strategy of picking "stars" from better departments as a strategy for growth compared to other approaches may end up paying too much for what they get as the new hire does not manage to keep the performance that she had in the previous more endowed institution. From a government policy perspective our results might indicate that the incentives for concentration (and consequently for mobility) introduced in the UK academic market in the past 20 years may not pay back either at the individual level or the system level. Indeed, even mobility to better institutions is associated with a very small individual performance premium that might not counterbalance the negative spillover on the less reputed department due to the departure of the star. Finally, our results indicate that policies encouraging mobility as a mechanism to facilitate knowledge creation and dissemination should be fine-tuned by distinguishing different types of mobility and by considering the individual cost that mobile researchers face. Organizations and policy makers could help to diminish the individual costs of mobility by offering more support to mobile researchers.

There are some caveats to these results due to the small number of observations. Although mobility is more frequent in the UK science system, it is difficult to build a complete career data set for a large sample of researchers. Due to the complexity involved in collecting full career information, and quantity and quality of research output, our sample is small in size and may not be representative. However, apart from the requirement for the faculty included in the sample to be research active (recipient of at least one EPSRC grant), we do not suspect the presence of bias linked to either research performance or mobility.

Finally, we do not really know much about academic salaries; we made an assumption (trying to provide some justification for it) that salary considerations are less relevant in this particular labor market. This assumption was probably true in the period of analysis, but since then the UK academic market, especially at the professorial level, has changed dramatically, making our assumption probably less sustainable at least in some academic fields.

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Appendix A: The PR Ranking Indicators

Following the approach used in Lawson and Soos (2014) we make use of the following two indicators to construct the ranking indicator:

1. raw number of publications for each HEI, each year (P(HEI, year)) and each of the two scientific categories;
2. relative impact (RI) of a university within the discipline, measured as the ratio of its mean citation rate to the world average.

$$RI(HEI, year) := \frac{C(HEI, year)/P(HEI, year)}{C(Total, year)/P(Total, year)} \quad (1)$$

We then construct an indicator that measures the Impact Weighted Productivity (IWP) of a given department per year, as the basis for our ranking indicator. IWP is the product of the two original measures and, thus, considers both department quality and research size within a specific subject field:

$$IWP =_{def} RI(HEI, year) \times P(HEI, year) = \frac{C(HEI, year)}{C(Total, year)/P(Total, year)}. \quad (2)$$

We calculate our research ranking indicator as percentile ranks (PR) based on the underlying distribution of IWP. Given the skewed distribution of the IWP indicator, percentile ranking is preferred to an ordinal scale which takes no account of ranking differences. We normalize IWPs linearly, dividing each value by the maximum value in the year and field. Thus, we measure the contribution of the particular HEI to the production of the UK sector relative to the highest contributor.

$$PR =_{def} \frac{IWP(HEI, year)}{\max\ (IWP(HEI, year))} = \frac{C(HEI, year)}{\max\ (C(HEI, year))}. \quad (3)$$

We consider *PR* over a 3-year period to adjust for possible annual fluctuations, bursts, or sudden decreases.

Appendix B: Robustness check estimations

Table B1. IV regression of performance (excluding lagged mobility variables)

MODEL VARIABLES	(1) NBREG-IV $PostMob_{it}$ PUB	(2) NBREG-IV $PostMob_{it}$ CIT5YR	(3) NBREG-IV $PostUniMob_{it}$ PUB	(4) NBREG-IV $PostUniMob_{it}$ CIT5YR
$PostMob_{it}$ / $PostUniMob_{it}$	0.237	1.128*	0.632	0.798
	(0.567)	(0.664)	(0.603)	(0.753)
AGE_{it}	0.061	0.006	0.063	0.034
	(0.051)	(0.067)	(0.054)	(0.068)
AGE_{it} 2	−0.001	0.000	−0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$FEMALE_i$	0.394	0.206	0.477	0.331
	(0.305)	(0.294)	(0.326)	(0.322)
Reference: $RANK1_{it-1}$				
$RANK2_{it-1}$	0.221	−0.009	0.161	0.122
	(0.205)	(0.219)	(0.236)	(0.266)
$RANK3_{it-1}$	0.311	−0.142	0.337	0.170
	(0.256)	(0.291)	(0.278)	(0.326)
$POSTDOC_i$	−0.372**	−0.359**	−0.518***	−0.352*
	(0.166)	(0.172)	(0.177)	(0.193)
$PATENT_{it-1}$	0.003	0.003	0.004	−0.007
	(0.021)	(0.022)	(0.021)	(0.023)
$UniRanking_{it-1}$			0.113	0.464*
			(0.193)	(0.239)
$LONDON_{it-1}$	−0.042	−0.415	0.050	−0.058
	(0.227)	(0.285)	(0.224)	(0.279)
Reference: $CHEMISTRY_i$				
$PHYSICS_i$	−0.320*	−0.447**	−0.245	−0.462**
	(0.165)	(0.199)	(0.175)	(0.232)
$COMPUTER_i$	−1.672***	−2.815***	−1.860***	−2.836***
	(0.209)	(0.271)	(0.269)	(0.365)
$MECHANICAL_i$	−1.152***	−1.992***	−1.171***	−2.040***
	(0.219)	(0.251)	(0.273)	(0.298)
Constant	0.132	3.466**	0.058	3.041**
	(1.063)	(1.365)	(1.197)	(1.482)
lnalpha	−0.663***	0.516***	−0.667***	0.489***
log Likelihood	−4584.344	−8713.545	−3959.726	−7511.935
Observations	1783	1783	1514	1514
Clusters	122	122	106	106
Smith−Blundell Test of Exogeneity (*P*-value)	0.060	0.897	0.035	0.174
Hansen's J statistic (p-value)	0.135	0.399	0.165	0.099

Robust clustered standard errors in parentheses; Year fixed effects in all models; $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$

Table B2. Effect of Mobility on Performance without controlling for endogeneity (naïve model)

MODEL VARIABLES	(1) NBREG PUB	(2) NBREG PUB	(3) NBREG CIT5YR	(4) NBREG CIT5YR
$PostMob_{it}$	0.284**	0.302**	0.324**	0.358**
	(0.120)	(0.126)	(0.154)	(0.161)
L. Mob_{it}		−0.279***		−0.167
		(0.102)		(0.154)
L2. Mob_{it}		−0.065		−0.007
		(0.097)		(0.150)
L3. Mob_{it}		−0.169		−0.319**
		(0.106)		(0.139)
AGE_{it}	0.072	0.045	0.064	0.050
	(0.046)	(0.049)	(0.058)	(0.064)
AGE_{it} 2	−0.001	−0.000	−0.001	−0.000
	(0.000)	(0.001)	(0.001)	(0.001)
$FEMALE_i$	0.393	0.319	0.171	0.049
	(0.300)	(0.289)	(0.274)	(0.265)
Reference: $RANK1_{it-1}$				
$RANK2_{it-1}$	0.217*	0.214*	0.130	0.156
	(0.126)	(0.126)	(0.167)	(0.164)
$RANK3_{it-1}$	0.324**	0.328**	0.142	0.169
	(0.164)	(0.162)	(0.219)	(0.219)
$POSTDOC_i$	−0.351**	−0.318**	−0.257	−0.239
	(0.147)	(0.147)	(0.162)	(0.164)
$PATENT_{it-1}$	0.002	0.002	−0.009	−0.009
	(0.017)	(0.017)	(0.019)	(0.018)
$LONDON_{it-1}$	−0.094	−0.059	−0.236	−0.246
	(0.211)	(0.213)	(0.253)	(0.253)
Reference: $CHEMISTRY_i$				
$PHYSICS_i$	−0.307**	−0.334**	−0.493***	−0.516***
	(0.154)	(0.154)	(0.189)	(0.198)
$COMPUTER_i$	−1.638***	−1.570***	−2.651***	−2.691***
	(0.198)	(0.193)	(0.284)	(0.292)
$MECHANICAL_i$	−1.167***	−1.148***	−2.114***	−2.141***
	(0.213)	(0.213)	(0.241)	(0.239)
Constant	−0.013	0.601	2.724**	2.973**
	(0.973)	(1.071)	(1.237)	(1.416)
lnalpha	−0.681***	−0.729***	0.533***	0.464***
log Likelihood	−4697.842	−4342.889	−8979.751	−8249.925
Observations	1850	1673	1850	1673
Clusters	124	122	124	122

Robust clustered standard errors in parentheses; Year fixed effects in all models; $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0$.