ISSN: 2039-4004

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WORKING PAPER SERIES

RESEARCHERS' MOBILITY AND ITS IMPACT ON SCIENTIFIC PRODUCTIVITY

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Working paper No. 13/2013

Università di Torino

Researchers’ mobility and its impact on scientific productivity

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Ver. 7.0, Dcember 2013

Acknowledgments
The authors are grateful to Cristiano Antonelli, Marco Guerzoni, Paul David, Jacques Mairesse, Fabio Montobbio, Lia Pacelli, Chiara Pronzato and Paula Stephan for comments and suggestions. Thanks are due also to Daniel Lopez Gonzales and Manuel Toselli for their contribution to the creation of the database. The paper has benefited from comments and suggestion received at the following seminar and conference presentations: Social Science and Technology Seminar, SIPER, Stanford University; SPRU, University of Sussex; DRUID Conference, Copenhagen; SEEK Conference, ZEW, Manheim and the EWEPA Conference, Verona. Financial support from the European Commission (FP7) Project ’An Observatorium for Science in Society based in Social Models – SISOB’ Contract no.: FP7 266588 and the Collegio Carlo Alberto Project ‘Researcher Mobility and Scientific Performance’ are gratefully acknowledged.

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Abstract

This article analyses the impact of mobility on researchers' performance. We develop a theoretical framework based on the job-matching approach and the idea that research productivity is driven by the availability of capital equipment (and human capital) for research, and peer effects. The empirical analysis studies the careers of a sample of 171 UK academic researchers, spanning 1957 to 2005. On the basis of a unique ranking of UK institutions that we were able to construct for the period 1982 to 2005, we develop an econometric analysis of the impact of job changes on post mobility performance over five-years, and the overall effect of mobility. Contrary to the assumptions underpinning most policy actions in this area, we find no evidence that mobility per se increases academic performance. Mobility to 'better' departments has a positive weakly significant impact, while downward mobility reduces researchers' productivity (in quantity and quality). Mobility is associated with a short-term decrease in performance arguably or most likely due to associated adjustment costs.

Keywords: Academic labour market, Research productivity, Researcher mobility

JEL codes: O31, I23, J24

1. Introduction

The UK university system has undergone a major restructuring since the 1980s. Starting from the introduction of the Research Assessment Exercise (RAE) in 1986, policy action has driven the system towards higher levels of concentration of research resources in a small number of research intensive universities (DES, 1991; HEFC, 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). Job mobility of researchers has been seen as a positive by-product of policy action, to be directly supported (HEFC, 1997).[1] Available data from the Higher Education Statistical Agency (HESA) spanning the period 1994-95 to 2005-06 (the latest year included in our database of UK scientists) show almost a doubling in the share of full time academics changing employment (moving to a different UK university, other universities abroad and business); some 2,600 academics changed jobs in the first period while about 5,100 in the last period.

Job mobility can give rise to both social and individual returns. Researcher mobility could be a mechanism of knowledge diffusion and generate positive spill-overs between firms, sectors, institutions and countries. By increasing the diffusion of ideas, researchers mobility may be positive for the research system as a whole. Several papers analyse these socially relevant benefits by focusing on the spill-over effect of mobility among firms (e.g. Cooper, 2001; Møen, 2005; Pakes and Nitzan 1983); sectors (e.g. Zucker et al., 1998, 2002; Crespi et al., 2007; Azoulay et al., 2011); academic institutions and countries –"peer effects"- (Moser et al., 2011; Borjas and Doran, 2012). Although more systematic investigation is required to properly understand the social returns of job mobility, studies on these have been more frequent. This paper departs from this literature and focuses on individual returns to academic mobility by assessing whether and how mobility to another university affects researchers' publication productivity. 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 mobility is a characteristic of productive researchers (van Heeringen and Dijkwel, 1987; Allison and Long, 1987). Some attention has also been devoted to the relationship between individual research productivity and international scientific mobility both at post-doctoral level (Canibano et al., 2008; Zubieta, 2009; Horta et al. 2010; Franzoni et al., 2012) and in general (Stephan and Levin, 2005; Hunter et al., 2009; Stephan, 2012; Franzoni et al., 2012). However, due to unavailability of data and difficulties in econometric modelling, these studies offer only very preliminary insights into the relationship between mobility and productivity.

[1] See Universities UK (2009) for an analysis of increased concentration of resources in the UK system in the period 1994-2007.

We develop a theoretical framework to predict the impact of job mobility on research productivity, based on a job-matching approach to academic labour mobility that emphasizes research and reputation factors. Science is a social system in which opportunities for research and the symbolic and material rewards for scientific enquiry tend to accumulate in a few individuals and institutions (Merton, 1968). This process leads to a structured system of production and access to resources and recognition. As is typical of structured systems, mobility across different levels of the scientific social structure becomes limited, which allows us to use this lower level of social mobility to check the quality and impact of transitions. Job changes to a higher quality/reputation institution could lead to better academic performance. 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 also perform an empirical analysis to address some of the shortcomings in the previous literature by focusing on the entire careers of a sample of mobile and immobile researchers. We estimate a series of econometric specifications of our model in a dynamic set up, to assess the impact of job changes on post-mobility output. We expect an initial decrease in performance associated with mobility costs, and a subsequent increase in performance, but only for those who move to higher reputation/quality institutions.

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 to 2005. The availability of reliable institutional-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 non-renewal of contract. Thus, a job change is the result of the researchers' decision.

We found no evidence that mobility per se boosts the publication productivity of researchers. What matters is where the move is 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 found strong evidence of short-term negative effects.

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

Labour market analyses based on job matching and the search theory model (Jovanovic, 1979; Mortensen, 1986) examine job changes in general; Zucker et al. (2002) examine the case of scientists, emphasizing the role of productivity for explaining mobility. However, there are only a few systematic studies that try to assess the other side of the relationship - whether mobility has a positive or negative impact on short- to mid-term scientific performance (Allison and Long, 1990). There is no systematic evidence of a causal effect between mobility and medium- to long-term researcher productivity.

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

$$sp = f(M, p, h) \qquad (1)$$

where M is mobility events, *p* is individual personal and academic characteristic and *h* is institution, field, country and time-specific environmental characteristics effecting scientific productivity.

Mobility may have a positive impact on research performance only if the researcher finds better conditions for pursuing her research endeavour; for example, if she moves to a new job in order 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 labour market (Section 2.1); in Section 2.2 we propose a framework to model the relationship between mobility and performance.

2.1. The academic labour market: Distinctive characteristics

Depending on the particular institutional setup,[2] the academic labour market is driven by traditional labour market factors, such as wage and search costs, contextualized to the academic market, and a set of academia-specific factors related to research and reputation. The most important labour market factors are: (1) wage related – the difference between current compensation and the new wage offer; (2) career related –promotion to associate or full professor usually associated with access to more resources for research, the possibility of hiring and directing doctoral and post-doctoral fellows, and a

[2] Such as the public servant position of academics in some European countries, a characteristic not discussed in this paper.

higher salary;[3] (3) opportunity related – non-permanent academic jobs are becoming more common in all countries and are associated with termination and non-renewal of contracts resulting in involuntary mobility; (4) 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;[4] (5) mobility cost related – the costs associated with mobility are not fixed and depend on mobility experience;[5] (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 introduces a gender and age bias.

Academic distinctive factors

The academic labour market is characterized by some distinctly academic factors, which are the focus of this paper. In the academic labour market research and "reputational" factors could be as, or even more, important than salary in the decision to accept or reject and 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 (positive utility) 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 include independent research. Hence, all else being equal, academics are willing to earn less in order 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 fewer teaching obligations, more research time, higher financial endowments, etc., 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 the benefits to outweigh the mobility costs), since research and reputation enter positively in her utility function. She can expect to increase 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)

[3] In some countries, e.g. Germany, it is often necessary to move to another university to achieve promotion to full professor.
[4] See the discussion of transfer markets for top scientists as a feature of the UK Research Assessment Exercise (Elton, 2000).
[5] 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).

are extremely high (Stephan, 2012). The researcher will benefit also from direct peer effects related to her new colleagues, and indirect effects from access to their social networks. 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 centres in order 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 The relationship between mobility and researcher's scientific performance

The relationship between mobility and researcher's scientific performance is bidirectional. To model it we need to understand the reasons of academic mobility to predict the impact of mobility on research performance. The probability of a job change (academic mobility) depends on the probability of receiving a job offer *f(.)* and the probability of accepting that job offer *g(.)*. Let us define:

$$f(\cdot) = f(s, e, p) \qquad (2)$$

$$g(\cdot) = g(w, b, c, r) \qquad (3)$$

In the typical search theory model, the probability of receiving an offer *f(.)* is likely to depend on factors such as search effort (s), and environmental (e) and individual (p) labour characteristics. The probability of accepting an offer *g(.)* 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 labour market distinctive factor (r) that takes account of the research and reputation related effects discussed in the previous section.

The probability of receiving a job offer *f(.)* depends decreasingly on search effort (s). The academic profession being an intrinsically networked job, the more connected the researcher to a densely populated network of public and private organizations the lower will be her search costs since she will be well informed about available positions. The extent of the individual's social network, therefore, increases her probability of receiving an offer *f(.)*. The probability of receiving a job offer *f(.)* also depends on environmental academic labour market characteristics (*e*) such as the existence of strong potential demand. Potential demand in terms of flexibility and density of the academic market is scientific field, country and time dependent. The researcher's personal characteristics (*p*) (such as PhD awarding institution, tenure, scientific productivity), which could be interpreted as signalling high individual productivity, positively affect the probability of receiving a job offer *f(.)*.

In traditional job change models, the probability of accepting an offer *g(.)* depends on the salary offered (*w*) and the retention strategy of the sending company which might offer a salary increase (*b)*; these factors can be affected by personal characteristics (*p)*. In academia, the higher the academic's position and longer the academic experience in that position, the higher will be the salary in the current job. However, 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, and less so in the UK (with the exception of business schools), 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 labour 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 very small role in explaining mobility. Thus, we can rewrite equation 3 as follows:

$$g(\cdot) = g(p, c, r) \qquad (4)$$

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).

Scientific performance (*sp*) is one of the personal characteristics 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 signalling a high quality researcher, increasing the probability of receiving an offer *f(.)* and decreasing the probability of accepting an offer *g(.)*.

Finally, 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(.)* 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.[6] 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.

At the same time, 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 rewrite the equations as follows:

$$f(.) = f(sp, s, e) \qquad (5)$$

$$g(.) = g\left(sp, pt, c(pf), r\right) \qquad (6)$$

$$M = f(\cdot) \times g(.) = f(sp, s, e) \times g\left(sp, pt, c(pf), r\right) \qquad (7)$$

We now turn to the impact of mobility on scientific productivity (*sp*). A job change can have an impact on the scientist's research performance after the move. 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 mobility are

[6] A related interpretation of mobility costs can be found in Shaw (1987).

associated with increased research productivity.

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, will move to a higher quality department with better endowed laboratories (better equipment, more junior research staff) and will, therefore, increase their performance.[7] 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 (Weinberg, 2007), 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 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 performance; 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

[7] 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.

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).[8]

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 (van Heeringen and Dijkwel, 1987; Shaw, 1987; Groysberg, 2008). Following a job change in laboratory-based work, the researcher can show decreased performance 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 performance due to adjustment costs

We estimate the following function:

$$sp = f(M, pt, pf, h) \tag{8}$$

where M is the mobility events, pt is individual academic characteristics such as career rank, pf is individual personal characteristics such as gender, and h is institution, field, country and time specific environmental characteristics affecting scientific productivity (e.g. there is a greater tendency to publish and cite more in medicine than in economics).

[8] 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 performance, 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. In a companion paper, we discuss the interaction between mobility and career progress, testing the hypothesis that a career move to professorial level will provide access to additional resources that might counterbalance the effect of moving to a lower ranked institution.

3. Empirical Analysis

3.1 The Sample

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.[9] We coded career information taken from CVs in order to construct comprehensive profiles for the researchers, spanning their careers from PhD award to 2005, resulting in a panel for the period 1957 to 2005. Our econometric analysis is limited to job changes that occurred between 1982 and 2005 because we needed to create an original institutional ranking variable based on publications and citations data which are reliable only after year 1982.

CV data are very useful for analysing academic careers since they provide information on job changes and also a reliable publications record (Cañibano and Bozeman, 2009). Using data collected from CVs combined with the ISI Web of Science (WoS) improved the accuracy of our data since it avoids mismatches arising from similar names and changes in researchers' institutional affiliations. Researchers' CVs include information on career paths and the timing and nature of job transitions.

In our analysis we focus on inter-institutional 'real' labour 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.[10] Thus, our analysis is limited to the influence of job mobility on productivity for researchers in tenured or tenure-track equivalent positions. Accordingly, in our analysis, postdoctoral mobility is not considered real labour mobility.[11] In the UK, the minimum tenure-track positions in academia are lecturer, followed by 'senior lecturer', 'reader' and 'professor'. Research fellow positions are considered a tenure-track equivalent to lecturer only if they continue for at least five years, indicating a long-term relationship with the university,

[9] The sample is based on a 2004 survey of academic researchers awarded a grant from the Engineering and Physical Sciences Research Council (EPSRC) at least once between 1999 and 2003, who therefore can be considered research active. CVs were collected for a subsample of survey respondents, and information on academic performance was complemented with information from online resources, e.g. ISI WoS. See Crespi et al. (2011) for a detailed description of the database.

[10] 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.

[11] Postdoctoral mobility and job mobility show very different patterns (Zubieta, 2009), due partly to contractual differences. Since the contractual relationship in research and postdoctoral fellow positions was not always clearly specified on CVs, it was difficult to distinguish research fellowships from postdoctoral stays; therefore, we considered researchers with 5 or more years in a research position as tenure track equivalent. The number and succession of postdoctoral and temporary positions prevent us from considering postdoctoral research stays as real labour mobility.

equivalent to a probation period. Academics in the UK are usually hired on permanent contracts (although since the 1990s there has been a large increase in short-term contracts at research fellow level), which, in the case of lecturer appointments or research fellowships, are subject to a three-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 (BIS, 2011; Ziman, 1991). 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 labour market very fluid.

Our sample consists of researchers aged 29 to 77, who were active in 2005. The mean age of the sample is 49 in 2005 (Figure 1). The first researcher joins our sample in 1957 and the last in 2003 (Figure 2). 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 (Figure 3). 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 (Figure 4).[12] 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. 50 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

[12] 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.

position in their country of birth, as indicated by the median distance between first permanent job and place of birth (176 miles).

CV information also allows us to clearly assign the WoS extracted publications to researchers. 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 (Figure 5) with a similar increase in publication quality. Quality is measured as number of WoS citations to a publication in the first five 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 paper attempts to measure.

3.2 Mobility and reputation

In the theoretical part of this paper, we stressed the importance of research and reputational factors for explaining the academic labour market. Access to resources and an improved research environment are incentives to move and are fundamental when analysing the impact of mobility on scientific productivity. In the period analysed in the paper, wages plaid a less important role in the UK academic labour market in particular because of the high level of standardization in UK academic salary scales. 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 in two main subject categories - natural sciences and engineering sciences - for the years 1982 to 2005.[13] 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 had access to two indicators (Lawson and Soos, 2014):

1) raw number of publications for each HEI, each year (P(HEI, year)) and each of the two categories;

2) relative impact (RI) of a university within the discipline, measured as the ratio of its mean citation rate to the world average.

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

$$RI(HEI, year) := \frac{C(HEI, year) / P(HEI, year)}{C(Total, year) / P(Total, year)} \quad (9)$$

We can 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:

$$IWP =_{def} RI(HEI, year) \times P(HEI, year) = \frac{C(HEI, year)}{C(Total, year) / P(Total, year)}. \quad (10)$$

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.

$$PR =_{def} \frac{IWP(HEI, year)}{\max(IWP(HEI, year))} = \frac{C(HEI, year)}{\max(C(HEI, year))}. \quad (11)$$

We consider *PR* over a three-year period to adjust for possible annual fluctuations, bursts or sudden decreases. This measure of research reputation for a 23-year panel can be constructed only for UK universities, that is, international institutions and firms are not included in the second part of the econometric analysis. 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.[14] 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.[15]

[14] See Lawson and Soos (2014) for a sensitivity analysis of this ranking.

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

Figure 6 shows the mean number of publications for the five years prior to and following the move. We plot the graph for: the immobile sample, for all moves between UK universities, for upward mobility, and for downward mobility. We assume a one-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 6 confirms the one-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 non-mobile researcher. An upwardly mobile researcher produces a higher number of publications even in the years before the move than a downward moving or non-mobile 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 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. Figure 6 depicts a graph that is consistent with the results in Allison and Long (1990) on the positive effects of department on productivity, but in contrast to their results, shows that the upward moving group starts out with higher productivity than the downward moving group.

Our econometric analysis looks at academic job changes between 1982 and 2005; it excludes mobility from companies (28 researchers). We excluded 19 researchers because of incomplete information on the year of promotion, leaving a sample of 124 researchers including international mobility, and 108 researchers in the case of within UK mobility

3.3 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:

$$E(sp'_{it} \mid M_{it}, X_{it}, c_i) = \exp\{\beta_1 M_{it} + \beta_2 X_{it} + c_i + \tau_t + \upsilon_{it}\} \qquad (12)$$

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 five years after job transition to investigate the evolution of post-mobility research performance.

The advantage of estimating pooled models is that they relax the strict fixed effects model assumption of exogeneity. 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. For example, the literature suggests that more able researchers have many more opportunities to change jobs because universities screen for ability and hire the most productive researchers. 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 pre-determined 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 modelling 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%[16] and the sample period feedback measure is hence defined as:

$$sp'stock_{it} = sp'_{it} - 1 + (1-\delta) sp'stock_{it-1} \qquad (13)$$

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.

However, 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 (Moser et al., 2013; Borjas and Doran, 2012). However, these are rare events that are of little policy relevance. Since mobility cannot be randomized, we adopt an instrumental variables (IV) approach (cf. Wooldridge, 2002a),[17]Finding plausible instruments is difficult, especially in the case of mobility and productivity, where one researcher's instrument might be another researcher's hypothesized cause of publication performance.[18] Dahl and Sorenson (2010) for a sample of Danish scientists and engineers show 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. We thus propose distance to place of birth as an instrument. Researchers living further away from their home town or country are more likely to move since such a move will incur lower social costs. We measure distance from home of 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

[16] Depreciation rates of 15% or 30% return similar results.
[17] 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 did not present an adequate technique.
[18] See Fernandez-Zubieta et al. (2014) for a discussion of alternative instrumental variables to study academic mobility.

the first permanent position and the researcher's place of birth.[19] The distance is measured in miles using Google Maps. For distances of more than 1,000 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. 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 1,105 miles (median is 219 miles).

[TABLE 1 ABOUT HERE]

3.4 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 five 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: (1) $PostMob_{it,}$, which switches from zero to 1 in the year of first mobility, clearly indicating the pre- and post-mobility periods; and (2) Mob_{it} that 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 we run an IV model in which the first equation explains job mobility using distance from place of birth (*Dis-Birth*) as the instrument

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: (1) *Upward Mobility* ($PostUP_{it}$, UP_{it}) defining a move to a higher ranked university, and (2) *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

[19] For 13 researchers we measured distance from city of high school education.

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 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 3.2 (*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 ABOUT HERE]

4.1. Main results

Table 2 shows the results for all (including international) mobility between higher education institutions. The number of observations in column 1 is 1,850 which reduces to 1,498 in column 3 due to longer lags that require a minimum of six observation years, i.e. consider only academics whose careers began before 2001.

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.[20] Column 2, which presents the yearly effects of the mobility shock, shows some evidence of a short-term negative effect. The results are similar for citation weighted output (Columns 3-4).

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 pre-sample means and dynamic feedback measures in models 1 and 2. Both measures are significant and positive in the publication

[20] We also analysed the difference in research performance between mobile and non-mobile researchers to investigate whether mobile researchers have a performance premium compared to non-mobile 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 non-mobile 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.

equation, while only the measure for dynamic stock is significant in the citations count equation. 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 reflects the stock of knowledge that is available ex-ante. 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 as the instrument. 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. The results of the instrumented model are presented in Table 2 Column 7.[21] The results show that also for the instrumented post-mobility indicator we find no significant effect on academic performance. The coefficient is close in sign and size to those in Columns 1 and 2. The results of the IV model confirm the robustness of the results from the feedback model.[22]

Thus, our first hypothesis of an initial negative effect on research performance is only weakly supported. We find no support for mobility having a positive impact on scientific performance.

[TABLE 3 ABOUT HERE]

4.2. Mobility between UK universities

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 24-year field-specific ranking that includes non-UK organizations. The number of observations reduces to 1,579 in Column 1 and 1,273 in Column 2.

Model 1 shows how publication performance changes after the mobility event. The mobility variable is positive, indicating that mobile academics perform better than non-mobile academics after mobility,

[21] Results of the IV-Model without mobility lags are presented in Appendix A Table A1.
[22] 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 A Table A2). This confirms the robustness of the approach.

but that the effect is insignificant. In column 2, which looks at the effects of the mobility shock, the post mobility variable turns significant. As in Table 2, there are indications of a weakly significant negative short-term effect. The results are similar for citation output (Columns 3-4). These results are confirmed in the IV model, but in both cases are insignificant.[23]

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

4.3 IV first stage – Mobility equation

Both Tables 2 and 3 present the first stage of our IV estimation (marginal effects in column 6). We find that our instrument has a positive and significant effect on mobility. The results 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 first mobility increases with rank, especially from lecturer to senior lecturer; researchers with post-doctoral experience are more likely to be mobile; and researchers working in London have a higher probability of first 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.

4.4 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 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 shows that

[23] Results of the IV model without mobility lags are presented in Appendix A Table A1.

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 ABOUT HERE]

The estimations for citations confirm the short- to medium-term negative effect of upward mobility and the expectation of a non-negative effect in later years. The university ranking control variable is positive in model 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 (belonging to a higher ranked department is associated with more citations).

Table 4 (Columns 5 to 8) reports the results for downward mobility (*DOWN*). They show that downward mobile researchers perform worse for publication numbers than their non-mobile peers, or colleagues who move to higher ranked institutions. This effect persists after isolating the short-term effect in Column 6. Thus, in the case of downward mobility, the initial negative effect of mobility does not diminish over the longer term.

The results for downward mobility are generally associated with reduced productivity - possibly due to reduced resources. However, for the majority (all but 4) 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. The negative signs are confirmed for the quality adjusted publications measure (Columns 7 and 8).[24]

For department quality, we find an additional positive effect for citations. This indicates that researchers moving to a lower quality institution but join 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 the mobility effect is conditioned by the nature of the job transition. The econometric analysis provides some weak evidence confirming

[24] 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.

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 analysed 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 upwards or downwards 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 to 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 labour market resembles the US system more than other European systems.

First, we analysed the difference in performance between mobile and non-mobile 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 some 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- to mid-term after the mobility event. These results contradict the view that mobility is associated with higher productivity, and challenges the assumptions underlying most policy initiatives that mobility to a higher research quality and more prestigious institution has a positive impact on individual research performance. Our results seems to be consistent with the view that scientists' mobility is driven by factors such as family related reasons, rather than strategies to enhance research performance (Franzoni et al., 2012).

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 dataset 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.

This study provides preliminary results for a small sample of UK researchers and original evidence related to mobility, challenging the commonly accepted policy view that mobility is beneficial and should be encouraged. Our results point to a complex interaction between mobility and productivity, which only in certain circumstances might result in a positive impact of the former on the latter. Mobility is far from been always beneficial for individual researchers, instead, mobility is associated with a short-term decrease in performance due to adjustment costs, while mobility to a lower ranked department seems to result in decreased performance also in the mid-term. Further research on the specificities of mobility, for example, mobility associated with career progress, mobility to and from business, mobility to a foreign country, and the career period in which the mobility occurs, is needed to properly assess the impact of mobility on scientific performance.

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Figures

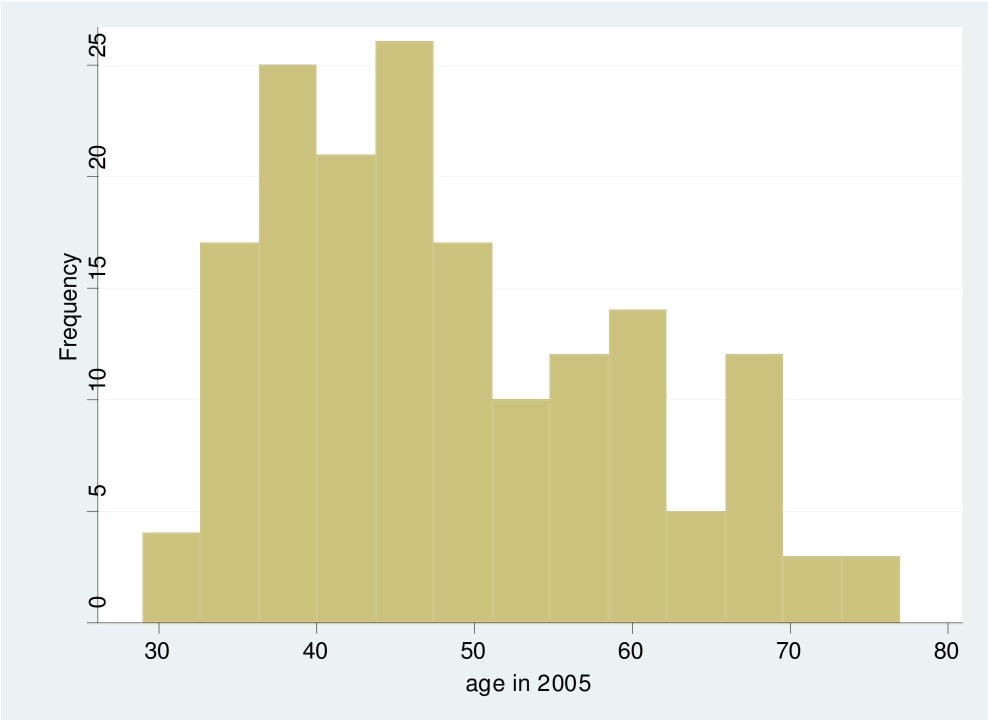

Figure 1: Age in 2005

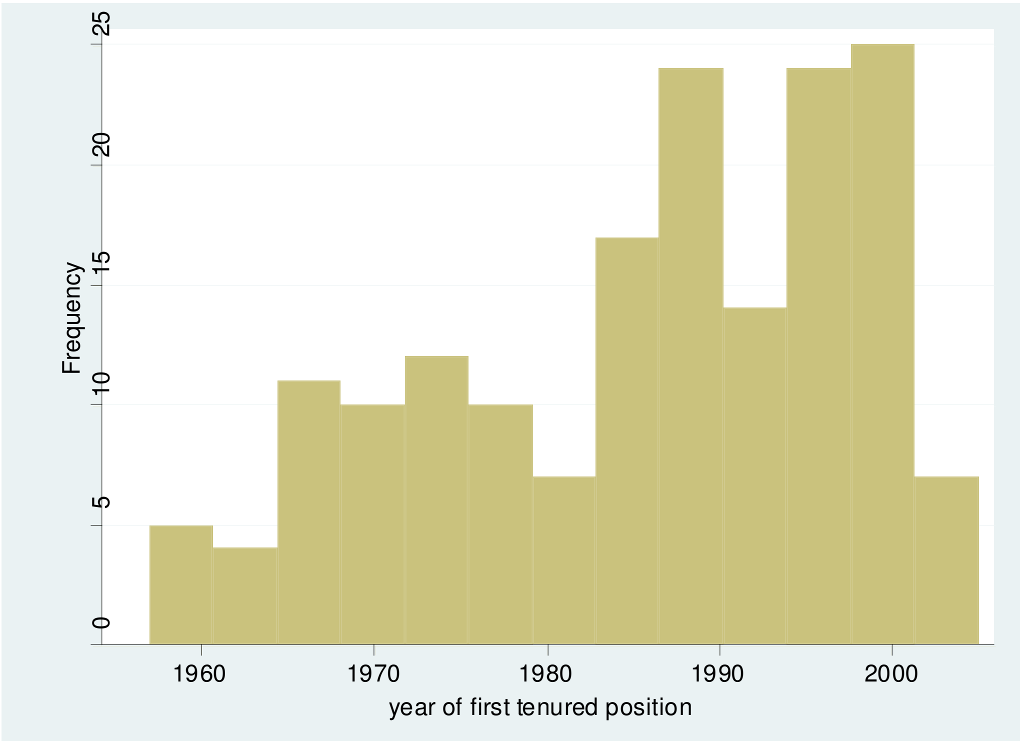

Figure 2: Year of first tenured position

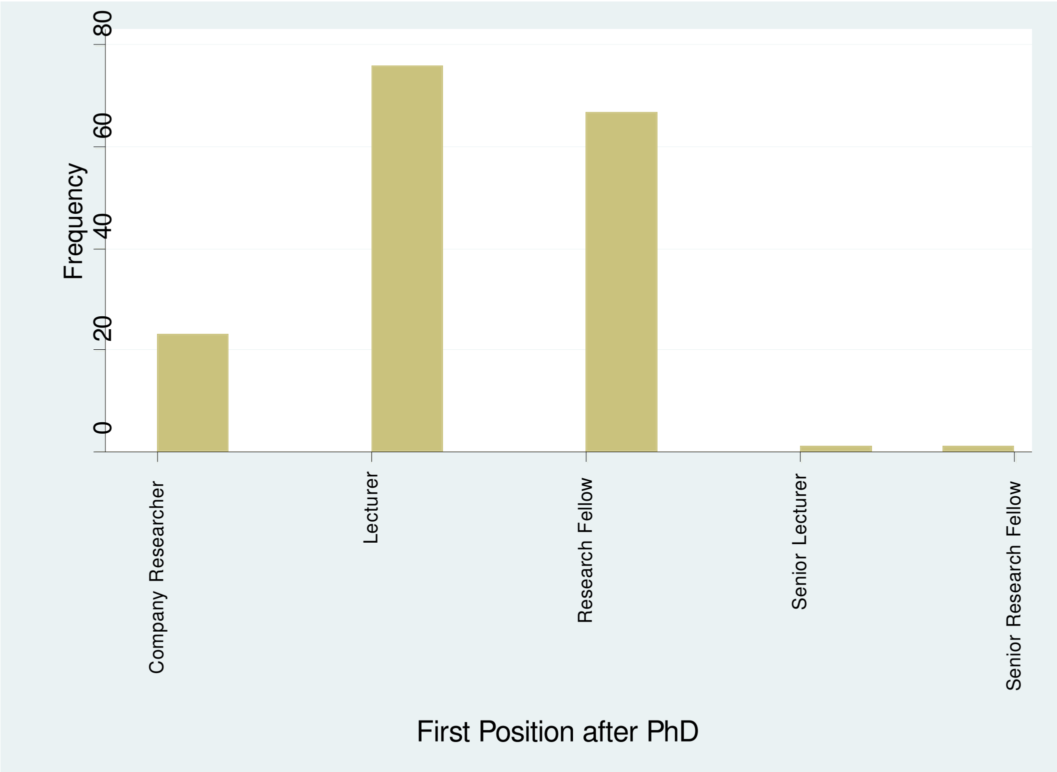

Figure 3: First position after PhD

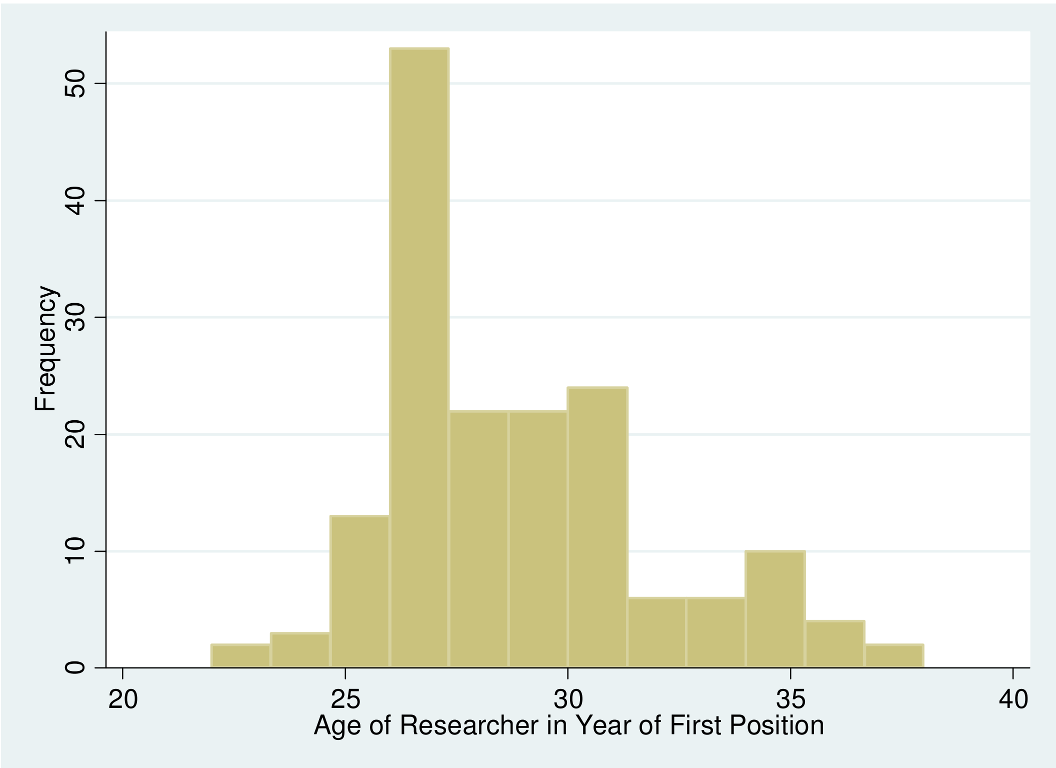

Figure 4: Age of researcher in year of first promotion

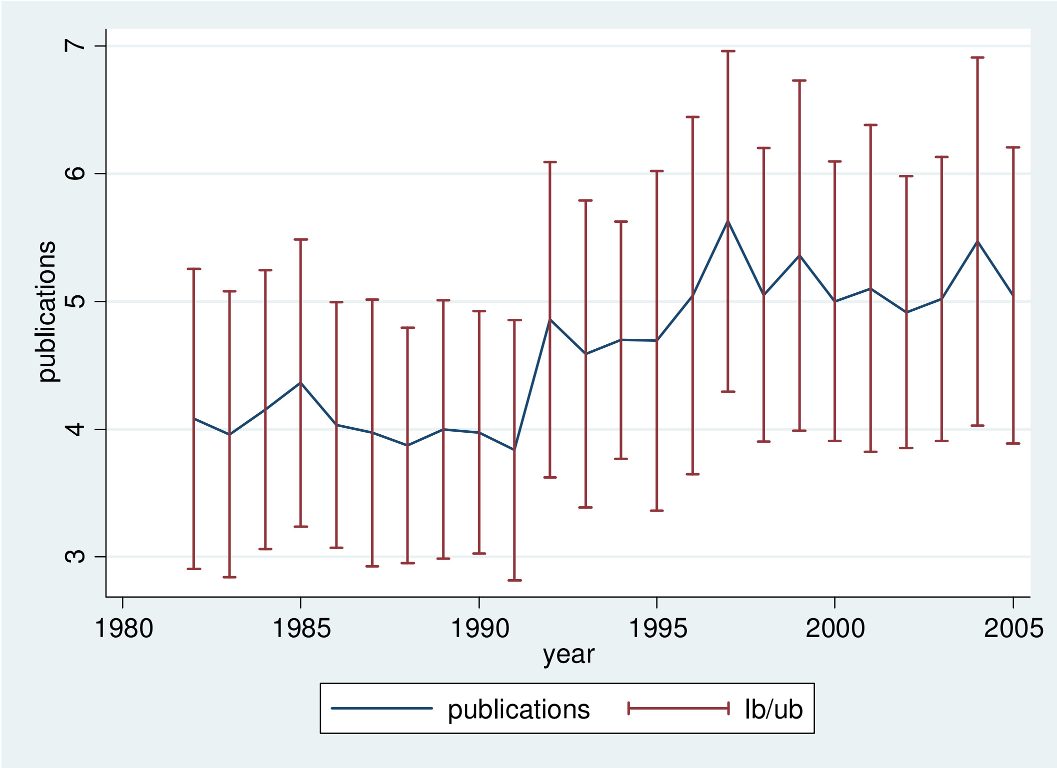

Figure 5: Average publication numbers

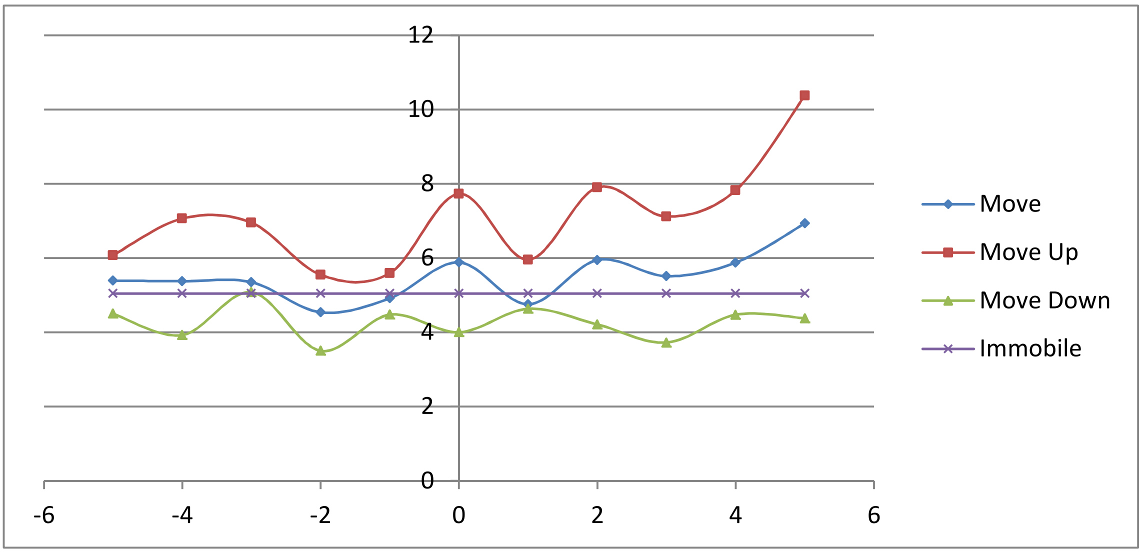

Figure 6: Publication numbers in years since move

Tables

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

		Full Sample of HE 1850 observations				Reduced Sample of UK-HEI 1579 observations			
VARIABLES	Definition	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 of distance between place of birth and first position	4.99	2.58	0.0	9	5.00	2.31	0.0	9
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. Feedback model and IV model.

MODEL	Non-instrumented with feedback measures (Blundell et al. 2002)				IV 1st stage Coef.	Marginal effects	IV 2nd stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NBREG	NBREG	NBREG	NBREG	LOGIT	LOGIT	NBREG-IV	NBREG-IV
VARIABLES	PUB	PUB	CIT5YR	CIT5YR	$PostMob_{it}$	$PostMob_{it}$	PUB	CIT5YR
Pre-sample Average (PUB/CIT)	0.115^{**}	0.121^{*}	0.005^{*}	0.002				
	(0.054)	(0.062)	(0.003)	(0.004)				
Stock (PUB/CIT)	0.013^{***}	0.012^{***}	0.001^{***}	0.001^{***}				
	(0.002)	(0.002)	(0.000)	(0.000)				
Dis_birth					0.101^{***}	0.016^{***}		
					(0.027)	(0.004)		
$PostMob_{it}$	0.088	0.126	0.105	0.133			0.174	0.965
	(0.069)	(0.082)	(0.096)	(0.100)			(0.768)	(0.911)
L. Mob_{it}		-0.215^{*}		-0.030			-0.155	-0.063
		(0.117)		(0.174)			(0.127)	(0.176)
L2. Mob_{it}		-0.037		0.026			0.126	0.270
		(0.103)		(0.163)			(0.132)	(0.227)
L3. Mob_{it}		-0.180		-0.315^{**}			-0.037	-0.224
		(0.120)		(0.151)			(0.125)	(0.160)
L4. Mob_{it}		-0.183^{*}		-0.209			-0.060	-0.128
		(0.109)		(0.183)			(0.113)	(0.188)
L5. Mob_{it}		-0.107		0.100			0.057	0.210
		(0.098)		(0.137)			(0.119)	(0.147)
AGE_{it}	0.039	0.012	0.083^{*}	0.079	0.158^{***}	-0.009^{***}	0.043	0.000
	(0.029)	(0.035)	(0.045)	(0.058)	(0.061)	(0.002)	(0.061)	(0.086)
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	-0.023	0.067	-0.014	-0.517^{**}	-0.084^{**}	0.268	0.148
	(0.135)	(0.090)	(0.135)	(0.134)	(0.224)	(0.036)	(0.289)	(0.280)
Reference: $RANK1_{it-1}$								
$RANK2_{it-1}$	0.089	0.088	-0.086	-0.018	1.309^{***}	0.193^{***}	0.241	0.071
	(0.076)	(0.079)	(0.131)	(0.123)	(0.198)	(0.027)	(0.253)	(0.269)
$RANK3_{it-1}$	0.070	0.076	-0.101	-0.046	1.955^{***}	0.307^{***}	0.322	-0.048
	(0.107)	(0.108)	(0.163)	(0.151)	(0.232)	(0.032)	(0.313)	(0.365)
$POSTDOC_i$	-0.133	-0.069	-0.017	0.072	0.413^{***}	0.067^{***}	-0.314^{*}	-0.319^{*}
	(0.090)	(0.083)	(0.110)	(0.110)	(0.132)	(0.021)	(0.181)	(0.193)
$PATENT_{it-1}$	-0.003	0.000	-0.002	-0.002	-0.067^{**}	-0.011^{**}	0.003	-0.000
	(0.007)	(0.007)	(0.010)	(0.010)	(0.027)	(0.004)	(0.021)	(0.025)
$LONDON_{it-1}$	-0.112	-0.045	-0.221	-0.212	1.808^{***}	0.293^{***}	0.014	-0.374
	(0.117)	(0.117)	(0.164)	(0.164)	(0.208)	(0.032)	(0.249)	(0.322)
Reference: $CHEMISTRY_i$								
$PHYSICS_i$	-0.075	-0.091	-0.127	-0.158	-0.461^{***}	-0.075^{***}	-0.366^{**}	-0.501^{**}
	(0.082)	(0.081)	(0.119)	(0.126)	(0.143)	(0.023)	(0.169)	(0.228)
$COMPUTER_i$	-0.953^{***}	-0.795^{***}	-1.742^{***}	-1.695^{***}	-0.173	-0.029	-1.555^{***}	-2.801^{***}
	(0.154)	(0.144)	(0.233)	(0.257)	(0.216)	(0.036)	(0.208)	(0.290)
$MECHANICAL_i$	-0.601^{***}	-0.532^{***}	-1.240^{***}	-1.154^{***}	-0.446^{**}	-0.073^{**}	-1.141^{***}	-2.005^{***}
	(0.172)	(0.154)	(0.221)	(0.210)	(0.188)	(0.030)	(0.223)	(0.269)
Constant	0.642	1.284	2.258^{**}	2.265^{*}	-3.771^{***}		0.552	3.546^{**}
	(0.670)	(0.836)	(0.999)	(1.340)	(1.364)		(1.261)	(1.736)
lnalpha	-1.208^{***}	-1.442^{***}	0.392^{***}	0.236^{**}			-0.733^{***}	0.422^{***}
log Likelihood	-4436.187	-3673.790	-8847.143	-7331.890	-887.183		-3954.525	-4436.187
Observations	1850	1498	1850	1498	1814		1498	1850
Clusters	124	113	124	113			113	124
Smith-Blundell Test of Exogeneity (p-value)							0.045	0.281
McFadden's R2					0.235			

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

TABLE 3: Effect of mobility between UK-HEI on publication performance. Feedback model and IV model.

MODEL	Non-instrumented with feedback measures (Blundell et al. 2002)				IV 1st stage Coef.	Marginal effects	IV 2nd stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NBREG	NBREG	NBREG	NBREG	LOGIT	LOGIT	NBREG-IV	NBREG-IV
VARIABLES	PUB	PUB	CIT5YR	CIT5YR	*$PostMob_{it}$*	*$PostMob_{it}$*	PUB	CIT5YR
Pre-sample Average (PUB/CIT)	0.109*	0.118*	0.004	0.002				
	(0.061)	(0.069)	(0.003)	(0.004)				
Stock (PUB/CIT)	0.013***	0.012***	0.001***	0.001***				
	(0.002)	(0.002)	(0.000)	(0.000)				
Dis_birth					0.105***	0.016***		
					(0.034)	(0.004)		
$PostMob_{it}$	0.114	0.199**	0.126	0.129			0.766	0.753
	(0.086)	(0.099)	(0.111)	(0.116)			(0.735)	(0.905)
L. *Mob_{it}*		-0.313**		0.001			-0.298**	-0.118
		(0.138)		(0.228)			(0.147)	(0.220)
L2. *Mob_{it}*		-0.168		-0.087			-0.036	-0.005
		(0.107)		(0.170)			(0.157)	(0.205)
L3. *Mob_{it}*		-0.270*		-0.332*			-0.148	-0.342
		(0.140)		(0.189)			(0.144)	(0.210)
L4. *Mob_{it}*		-0.174		-0.006			-0.072	0.040
		(0.132)		(0.204)			(0.129)	(0.222)
L5. *Mob_{it}*		-0.165		0.170			-0.027	0.244
		(0.110)		(0.177)			(0.130)	(0.187)
AGE_{it}	0.036	0.002	0.089*	0.096	0.010	-0.011***	0.034	0.031
	(0.031)	(0.037)	(0.047)	(0.059)	(0.076)	(0.002)	(0.063)	(0.084)
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	-0.026	0.150	-0.003	0.194	0.029	0.382	0.298
	(0.157)	(0.109)	(0.171)	(0.166)	(0.223)	(0.033)	(0.323)	(0.304)
Reference: $RANK1_{it-1}$								
$RANK2_{it-1}$	0.106	0.096	-0.036	-0.002	1.677***	0.219***	0.153	0.155
	(0.084)	(0.090)	(0.142)	(0.141)	(0.233)	(0.026)	(0.265)	(0.310)
$RANK3_{it-1}$	0.144	0.146	0.002	0.005	2.057***	0.283***	0.317	0.200
	(0.130)	(0.128)	(0.184)	(0.181)	(0.286)	(0.034)	(0.304)	(0.365)
$POSTDOC_i$	-0.186*	-0.091	-0.017	0.143	0.396***	0.059***	-0.463**	-0.274
	(0.103)	(0.093)	(0.125)	(0.125)	(0.149)	(0.022)	(0.190)	(0.216)
$PATENT_{it-1}$	-0.003	0.000	-0.004	-0.006	-0.034	-0.005	0.004	-0.013
	(0.008)	(0.007)	(0.013)	(0.012)	(0.024)	(0.004)	(0.021)	(0.025)
$UniRanking_{it-1}$	0.053	0.087	0.311**	0.231	-0.650***	-0.097***	0.171	0.411
	(0.107)	(0.119)	(0.144)	(0.170)	(0.242)	(0.036)	(0.205)	(0.271)
$LONDON_{it-1}$	-0.074	-0.058	-0.193	-0.235	1.177***	0.176***	0.041	-0.079
	(0.141)	(0.133)	(0.199)	(0.188)	(0.219)	(0.032)	(0.232)	(0.285)
Reference: $CHEMISTRY_i$								
$PHYSICS_i$	-0.063	-0.092	-0.157	-0.198	-0.631***	-0.095***	-0.291	-0.561**
	(0.088)	(0.091)	(0.133)	(0.146)	(0.162)	(0.024)	(0.190)	(0.275)
$COMPUTER_i$	-1.133***	-0.852***	-1.860***	-1.642***	-1.053***	-0.148***	-1.662***	-2.713***
	(0.197)	(0.209)	(0.292)	(0.331)	(0.260)	(0.032)	(0.290)	(0.429)
$MECHANICAL_i$	-0.640***	-0.543***	-1.320***	-1.231***	-0.353	-0.055	-1.130***	-2.075***
	(0.215)	(0.191)	(0.255)	(0.227)	(0.227)	(0.035)	(0.275)	(0.296)
Constant	0.798	1.525*	2.086**	1.781	-0.502		0.541	2.909
	(0.711)	(0.893)	(1.053)	(1.384)	(1.686)		(1.406)	(1.802)
lnalpha	-1.174***	-1.405***	0.362***	0.208**			-0.729***	0.399***
log Likelihood	-3855.741	-3188.883	-7651.487	-6328.996	-707.631		-3424.171	-6456.034
Observations	1579	1273	1579	1273	1550		1273	1273
Clusters	108	97	108	97			97	97
Smith-Blundell Test of Exogeneity (p-value)							0.015	0.121
McFadden's R2					0.219			

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

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**	0.139**	0.004*	0.003	0.128**	0.149**	0.005*	0.003
	(0.062)	(0.069)	(0.003)	(0.004)	(0.057)	(0.064)	(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	0.421***	0.011	0.237	-0.173*	-0.267**	-0.061	-0.316*
	(0.135)	(0.125)	(0.172)	(0.163)	(0.096)	(0.114)	(0.144)	(0.185)
L. UP_{it} / L. $DOWN_{it}$		-0.505**		-0.184		0.179		0.695*
		(0.205)		(0.326)		(0.234)		(0.419)
L2. UP_{it} / L2. $DOWN_{it}$		-0.430**		-0.613**		0.027		0.140
		(0.203)		(0.263)		(0.208)		(0.260)
L3. UP_{it} / L3. $DOWN_{it}$		-0.574***		-0.413		-0.297		-0.286
		(0.201)		(0.318)		(0.186)		(0.309)
L4. UP_{it} / L4. $DOWN_{it}$		-0.512**		-0.671**		0.059		0.168
		(0.217)		(0.292)		(0.190)		(0.308)
L5. UP_{it} / L5. $DOWN_{it}$		-0.461**		-0.009		0.040		0.480
		(0.201)		(0.270)		(0.199)		(0.371)
AGE_{it}	0.036	0.012	0.088*	0.096	0.037	0.008	0.088*	0.107*
	(0.031)	(0.034)	(0.047)	(0.058)	(0.032)	(0.038)	(0.047)	(0.057)
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	-0.008	0.151	0.007	0.187	-0.040	0.148	0.001
	(0.155)	(0.108)	(0.168)	(0.164)	(0.154)	(0.109)	(0.166)	(0.165)
Reference: $RANK1_{it-1}$								
$RANK2_{it-1}$	0.121	0.090	-0.001	0.010	0.155*	0.129	0.007	0.041
	(0.082)	(0.090)	(0.136)	(0.142)	(0.086)	(0.092)	(0.141)	(0.144)
$RANK3_{it-1}$	0.186	0.156	0.033	0.011	0.210	0.181	0.042	0.049
	(0.128)	(0.127)	(0.182)	(0.182)	(0.134)	(0.129)	(0.187)	(0.187)
$POSTDOC_i$	-0.190*	-0.088	-0.009	0.142	-0.180*	-0.078	-0.010	0.154
	(0.103)	(0.091)	(0.127)	(0.127)	(0.103)	(0.089)	(0.128)	(0.128)
$PATENT_{it-1}$	-0.001	0.002	-0.004	-0.005	-0.002	0.002	-0.003	-0.003
	(0.009)	(0.008)	(0.013)	(0.012)	(0.010)	(0.010)	(0.014)	(0.013)
$UniRanking_{it-1}$	0.016	0.048	0.296**	0.204	0.026	0.045	0.288**	0.199
	(0.097)	(0.112)	(0.144)	(0.171)	(0.109)	(0.122)	(0.147)	(0.176)
$LONDON_{it-1}$	-0.106	-0.090	-0.166	-0.215	-0.035	-0.038	-0.161	-0.232
	(0.138)	(0.128)	(0.197)	(0.189)	(0.141)	(0.130)	(0.193)	(0.180)
Reference: $CHEMISTRY_i$								
$PHYSICS_i$	-0.055	-0.078	-0.163	-0.197	-0.087	-0.122	-0.166	-0.223
	(0.086)	(0.087)	(0.132)	(0.147)	(0.089)	(0.091)	(0.131)	(0.144)
$COMPUTER_i$	-1.123***	-0.832***	-1.893***	-1.674***	-1.162***	-0.913***	-1.903***	-1.730***
	(0.196)	(0.208)	(0.286)	(0.320)	(0.189)	(0.195)	(0.285)	(0.326)
$MECHANICAL_i$	-0.632***	-0.547***	-1.297***	-1.233***	-0.651***	-0.575***	-1.295***	-1.251***
	(0.215)	(0.185)	(0.258)	(0.225)	(0.222)	(0.196)	(0.259)	(0.227)
Constant	0.791	1.291	2.125**	1.797	0.791	1.391	2.129**	1.544
	(0.707)	(0.837)	(1.053)	(1.366)	(0.734)	(0.915)	(1.056)	(1.343)
lnalpha	-1.181***	-1.442***	0.364***	0.207**	-1.178***	-1.404***	0.363***	0.204*
log Likelihood	-3853.608	-3180.768	-7652.747	-6328.253	-3854.932	-3186.457	-7652.574	-6326.287
Observations	1579	1273	1579	1273	1579	1273	1579	1273
Clusters	108	97	108	97	108	97	108	97

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

Table A1: IV regression of performance (excluding lagged mobility variables)

	(1)	(2)	(3)	(4)
MODEL	NBREG-IV	NBREG-IV	NBREG-IV	NBREG-IV
	$PostMob_{it}$	*$PostMob_{it}$*	*$PostUniMob_{it}$*	*$PostUniMob_{it}$*
VARIABLES	PUB	CIT5YR	PUB	CIT5YR
$PostMob_{it}$ / $PostUniMob_{it}$	-0.055	0.429	0.614	0.882
	(0.730)	(0.960)	(0.662)	(0.813)
AGE_{it}	0.080	0.047	0.071	0.043
	(0.050)	(0.072)	(0.051)	(0.065)
AGE_{it} 2	-0.001	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$FEMALE_i$	0.377	0.172	0.478	0.341
	(0.301)	(0.289)	(0.324)	(0.316)
Reference: $RANK1_{it-1}$				
$RANK2_{it-1}$	0.289	0.107	0.176	0.100
	(0.235)	(0.253)	(0.253)	(0.289)
$RANK3_{it-1}$	0.418	0.065	0.350	0.139
	(0.299)	(0.355)	(0.296)	(0.350)
$POSTDOC_i$	-0.333*	-0.276	-0.496***	-0.336*
	(0.172)	(0.187)	(0.177)	(0.193)
$PATENT_{it-1}$	-0.001	-0.005	0.003	-0.007
	(0.021)	(0.024)	(0.021)	(0.023)
$UniRanking_{it-1}$			0.112	0.469**
			(0.188)	(0.233)
$LONDON_{it-1}$	0.044	-0.217	0.039	-0.095
	(0.252)	(0.348)	(0.228)	(0.287)
Reference: $CHEMISTRY_i$				
$PHYSICS_i$	-0.337**	-0.481**	-0.241	-0.448*
	(0.166)	(0.206)	(0.175)	(0.233)
$COMPUTER_i$	-1.643***	-2.680***	-1.820***	-2.738***
	(0.206)	(0.280)	(0.263)	(0.352)
$MECHANICAL_i$	-1.190***	-2.068***	-1.181***	-2.037***
	(0.226)	(0.266)	(0.275)	(0.301)
Constant	-0.158	2.885**	-0.162	2.765*
	(1.017)	(1.351)	(1.157)	(1.418)
lnalpha	-0.656***	0.542***	-0.660***	0.508***
log Likelihood	-4714.284	-8988.495	-4085.658	-7769.672
Observations	1850	1850	1579	1579
Clusters	124	124	108	108
Smith-Blundell Test of Exogeneity (p-value)	0.045	0.281	0.015	0.121

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

Table A2: Effect of Mobility on Performance without controlling for endogeneity (naïve model)

	(1)	(2)	(3)	(4)
MODEL	NBREG	NBREG	NBREG	NBREG
VARIABLES	PUB	PUB	CIT5YR	CIT5YR
$PostMob_{it}$	0.284**	0.368***	0.324**	0.390**
	(0.120)	(0.141)	(0.154)	(0.184)
L. Mob_{it}		-0.354***		-0.268
		(0.129)		(0.177)
L2. Mob_{it}		-0.095		-0.007
		(0.123)		(0.205)
L3. Mob_{it}		-0.245**		-0.420***
		(0.125)		(0.159)
L4. Mob_{it}		-0.261**		-0.351*
		(0.115)		(0.180)
L5. Mob_{it}		-0.139		0.015
		(0.113)		(0.132)
AGE_{it}	0.072	0.043	0.064	0.048
	(0.046)	(0.052)	(0.058)	(0.071)
AGE_{it} 2	-0.001	-0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
$FEMALE_i$	0.393	0.279	0.171	0.130
	(0.300)	(0.278)	(0.274)	(0.266)
Reference: $RANK1_{it-1}$				
$RANK2_{it-1}$	0.217*	0.251*	0.130	0.228
	(0.126)	(0.136)	(0.167)	(0.164)
$RANK3_{it-1}$	0.324**	0.349**	0.142	0.243
	(0.164)	(0.165)	(0.219)	(0.211)
$POSTDOC_i$	-0.351**	-0.314**	-0.257	-0.237
	(0.147)	(0.148)	(0.162)	(0.170)
$PATENT_{it-1}$	0.002	0.002	-0.009	-0.011
	(0.017)	(0.016)	(0.019)	(0.019)
$LONDON_{it-1}$	-0.094	-0.045	-0.236	-0.236
	(0.211)	(0.213)	(0.253)	(0.263)
Reference: $CHEMISTRY_i$				
$PHYSICS_i$	-0.307**	-0.351**	-0.493***	-0.553***
	(0.154)	(0.156)	(0.189)	(0.212)
$COMPUTER_i$	-1.638***	-1.542***	-2.651***	-2.765***
	(0.198)	(0.202)	(0.284)	(0.315)
$MECHANICAL_i$	-1.167***	-1.123***	-2.114***	-2.090***
	(0.213)	(0.212)	(0.241)	(0.248)
Constant	-0.013	0.636	2.724**	2.976*
	(0.973)	(1.159)	(1.237)	(1.603)
lnalpha	-0.681***	-0.769***	0.533***	0.414***
log Likelihood	-4697.842	-3937.126	-8979.751	-7469.745
Observations	1850	1498	1850	1498
Clusters	124	113	124	113

Robust clustered standard errors in parentheses; Year fixed effects in all models; *** p<0.01, ** p<0.05, * p<0.