Paper to be presented at the DRUID 2012

on

June 19 to June 21

at

CBS, Copenhagen, Denmark,

Researchers' mobility and its impact on scientific productivity

Ana Fernandez-Zubieta
Spanish Council for Scientific Research
Institute for Advanced Social Studies
afernandez-zubieta@iesa.csic.es

Aldo Geuna
University of Turin
Department of Economics S. Cognetti De Martiis
aldo.geuna@unito.it

Cornelia Lawson
University of Turin
Department of Economics S. Cognetti De Martiis
cornelia.meissner@unito.it

Abstract

This article analyses the impact of mobility on researcher productivity. We address the relationship by developing a theoretical framework based on the job-matching approach for academics and the idea that productivity is driven by capital availability and peer effects. The empirical analysis is based on the entire careers of a sample of 171 UK academic researchers, spanning from 1957 to 2005. We analyse the impact of job changes on post mobility output in 3 and 6 year periods. Contrary to common wisdom, we do not find evidence that mobility per se increases academic performance. Mobility to better departments has a positive but weakly significant impact while downward mobility results in decreasing researchers? productivity. Once we control for mobility associated with career progress, the results indicate significant strong positive impact for mobility to higher quality department. We estimated a set of alternative specifications of mobility finding evidence of an increase of productivity for mobility from industry to academia but only after an initial negative effect. In most cases mobility is associated with short-term decrease of productivity due to hypothesised adjustment costs.

Jelcodes:O31,I23

1. Introduction

The establishment of research networks and the mobility of researchers across different countries, fields and sectors has been identified as a major policy goal in recent years. In the EU, the commitment to develop a European Research Area (ERA) also implies the promotion of "greater mobility of researchers" (EC, 2001: 1; EC, 2010: 11, 17). National reports additionally point out the need for greater intra-national mobility and flexibility of researchers for knowledge diffusion between different institutions and sectors (e.g. CST, 2010). These policy papers assume that scientists' mobility facilitates knowledge and technology transfer, the creation of networks and the increase in productivity. However, very few systematic studies have been carried out to measure the impact of mobility on individual productivity.[1]

Whether and how mobility affects researchers' productivity, the focus of this paper, has yet to be properly explored. A few academic papers have analysed spill-over and peer effects resulting from the movement of academics (Cooper, 2001; Møen, 2005; Pakes & Nitzan 1983; Zucker et al., 1998, 2002), while very little attention has been given to the analysis of the consequences for researchers themselves, with the exception of a few papers in the sociology of science (see for example Alison and Long, 1990). The sociology of science approached this topic much earlier and found some weak evidence of a negative impact of immobility (Hargens and Farr, 1973) and some evidence suggesting that mobility is a characteristic of productive researchers (van Heeringen and Dijkwel, 1987; Alison and Long, 1987). Dietz and Bozeman (2005) worked on intersectorial mobility, finding weak evidence of some positive effect on productivity. Due to data availability and modelling difficulties, these studies offer only a very preliminary insight into the relationship between mobility and productivity without providing either a comprehensive theoretical framework or a full econometric modelling strategy.

In order to analyse the relationship, firstly, we develop a theoretical framework based on the job-matching approach for academics where research and reputation factors are emphasized. Science is a social system in which opportunities for research and the symbolic and material rewards for its inquiry tend to be accumulated in few individuals and institutions (Merton, 1968). This process leads to a structured system of production, access to resources and recognition. As in all structured systems, mobility across different levels of scientific social structure is limited. Therefore, it is possible to use this limited social mobility to check the quality and impact of the transitions. Job

[1] A large number of works have been devoted to the analysis of mobility of researchers in term of brain drain versus brain gain/circulation. See, among others Meyer (2001) for a review of the literature and UNESCO (2005) for a policy oriented analysis.

changes to a higher quality/reputation institution could lead to better academic performance. The idea of productivity being driven by capital availability and peer effects lead us to expect medium-term positive effect of mobility on productivity only for job changes that imply a move to a higher quality/reputation institution. In our framework a change of job is always associated to a short term reduction of productivity due to adjustment or disruption costs.

Secondly, we perform an empirical analysis that tries to address the shortcomings of previous literature by focussing on the entire careers of a sample of mobile and immobile researchers. We estimate in a dynamic set up a series of econometric specifications of the model to assess the impact of mobility on the short to medium term productivity of researchers. Specifically we focus on the impact of job changes on the post mobility output in the 3 and 6 year intervals following job mobility, expecting an initial decrease in productivity associated with mobility costs followed by an increase only for those who move to higher reputation/quality institutions. As many factors can confound the correlation between mobility and productivity, we devote particular emphasis to qualify types of mobility as this relates to the reasons for moving. In this paper we focus on estimating model specifications that consider the rank of the sending and receiving institution controlling for the career progress associated with the mobility and the transition to and from employment in a company.

The empirical analysis is based on a unique database that includes detailed information regarding employment patterns and publishing activities of a sample of UK academic researchers since their first professional appointment, spanning the years 1957 to 2005 in science and engineering. In our sampling strategy we focus only on researchers that were in a “tenure like” position, that’s to say we do not include mobility due to non renewal of the contract. Researchers that changed job decided to do so. We find no evidence that mobility per se helps to increase the productivity of researchers. Mobility to lower ranked universities is accompanied by a decrease in publication numbers while upward mobility is weakly associated with a positive increase in productivity. Only mobility to a higher ranked department associated with promotion is strongly linked to an increase in productivity. Contrary to expectations that mobility to a better position in a lower quality department would increase publication output, which is derived from policy documents, downward mobility always has a negative impact on productivity, even in the case of a job change associated with a promotion. We run a set of alternative specifications of mobility with some interesting results: mobility from industry to academia has an initial negative effect that becomes positive after a period of adjustment.

The remainder of this paper is organized as follows: Section 2 provides a brief review of the literature and offers a broad framework to study the impact of mobility on researcher's productivity; Section 3 presents the research design and Section 4 the results and some robustness checks; finally Section 5 concludes, discussing limitations of current modelling and future development of this research area.

2. What do we know of researcher productivity and mobility?

Labour market analyses based on job matching and the search theory model (Jovanovic, 1979 and Mortensen, 1986) has examined job changes in general and, more recently, in the case of scientists (Zucker, et. al, 2002) emphasizing, in the latter case, the role of productivity in explaining mobility. However, only few systematic studies have tried to assess the other side of the relationship; whether mobility has a positive or negative impact on short term scientific productivity (Alison and Long, 1990) and no systematic evidence is provided of a causal effect between mobility and medium to long term productivity of researchers.

This papers looks at the academic labour market with the aim of examining the impact of mobility on scientific productivity based on a job-matching framework. While the importance of the phenomenon (the positive effect of mobility on productivity) has repeatedly been emphasised,[2] problems of data availability and modelling difficulties have made its systematic analysis very difficult. This paper is a first attempt to provide a comprehensive framework to model the relationship with an application to the case of a sample of UK scientists.

Mobility might assert a positive impact on productivity only if the researcher finds better conditions to pursue her research endeavour, hence she moves to a new job to increase her research performance. However, there are other reasons justifying mobility that are not related to research performance, for example, wage, family concerns, etc. To fully understand the impact of mobility on productivity we first need to understand the drivers of researchers' mobility, and then model the impact of mobility on productivity controlling for those factors that could have a confounding effect. Below, first we briefly review the main tenets of the literature on the drivers of mobility and discuss the specificities of the academic labour market (Section 2.1); second we provide a framework to model the relationship between mobility and productivity (Section 2.2).

2.1. The academic labour market

[2] See the large body of policy literature and policy actions concerning mobility of researchers (e.g. EC, 2010)

Job changes in academia are driven by traditional factors associated with any job change such as wage and search costs and by a set of academic specific factors that are related to research and reputation. Setting aside redundancy, the wage received is the single most important determinant of the choice of accepting/leaving a business job. This is not the case in the academic labour market, where other research and "reputational" factors are crucial. For academics, research (time and support) is the most important aspect of their job satisfaction entering positively in their utility function while at the same time being a work activity that produces outputs. The time spent doing research is partially perceived by academics as leisure (consumption) time, resulting in their willingness to forego higher wages available in business jobs where independent research is not pursued. Hence, academics are willing to earn less, everything else being equal, to be able to do research (Stern, 2004; Sauermann and Roach, 2011). Another important factor in the utility function of a researcher is her reputation, which is affected by institutional reputation (to simplify we do not distinguish between department and university). A researcher values working in a highly prestigious institution because of direct benefits, such as fewer teaching obligations, more research time, higher financial endowments, etc., but also for positive externalities attached to these positions (she works there she must be good!) These are important in the market for science in which individual quality assessment is not easy, especially in the early phase of the career, and prices -publications- are not perfect carriers of information.

Depending on different institutional set ups such as the public servant role of academics in some European countries, not discussed in this paper, the academic labour market is driven by traditional labour market factors contextualized to the academic market and academic specific factors. Among the former the most important are: (1) wage related – the difference between current compensation and new wage offer (particularly relevant for a move to a business job, usually associated with a much higher salary); (2) career related – a promotion to associate or full professor usually associated with a higher salary[3]; (3) employment opportunity related – non-permanent academic jobs are getting more common in all countries, these are associated with termination and non-renewal resulting in involuntary mobility; (4) market related –the fluidity of the job market differs across countries and disciplinary fields and the thickness of the market varies depending on the time period;[4] (5) mobility cost related – the relevance of costs associated with mobility is not fixed and

[3] In some countries, for example Germany, one usually needs to move to a different university to gain full professorship.
[4] See the discussion of transfer markets for top scientists as a feature of the Research Assessment Exercise in the UK (Elton, 2000).

depends on previous mobility experience;[5] (6) family related reasons – partners moving, ageing parents and children's education related considerations can be common reasons for involuntary mobility and may reduce the propensity to move introducing a gender and age bias.

Academic specific factors

Academic labour market can further be explained by academic specific factors, which are the focus of this paper. We identify the three main factors. First, everything else being equal, an academic will move to a better-ranked institution (expecting benefits higher than the mobility costs), as research and reputation enters positively in her utility function. She can expect to increase performance in a higher ranked institution as there will be better capital availability, crucial in the natural and biomedical sciences, where laboratory costs are extremely high, both, in terms of equipment and human capital. She will also benefit from peer effects both through her new colleagues directly or through access to their social networks. Moreover, due to institutional reputation, she could have a higher probability of having future contractual research financed, as in the context of funding agency selection, where there are more excellent proposals than budget available, institutional reputation could matter in the final selection.

Second, especially in new and fast changing disciplines, mobility is driven by the prospect of accessing tacit knowledge and new equipment. In an early phase of development of a new discipline, knowledge is located in a small number of laboratories, where the original discoveries happened. Through publications this knowledge percolates through the university system but, especially due to the invention of new equipment (see for example the case of the production of the onco-mouse, Murray, 2011), some knowledge remains "sticky" to a laboratory and can only be passed on through training and equipment use. Researchers are willing to bear the costs of a move to such centres to acquire the tacit knowledge held there. This can happen through short stays (such as during a sabbatical leave) or with a job change.

Third, academic mobility is strongly affected by the relative opportunity advantage. In a market with a clear reputation/quality ranking, researchers working in high rank institutions have a much lower probability of moving, everything else being equal.

[5] First time mobility is the most costly (leaving home effect), multiple job changes are associated with learning by doing, which decreases mobility costs (for example, foreigners or national with foreign PhD will have lower mobility costs).

2.2 The relationship between mobility and researcher's scientific productivity

The relationship between mobility and researcher's productivity is bidirectional. To model it we need to look at the probability of a job change as depending on the probability of receiving a job offer *f(.)*, and the probability of accepting that job offer *g(.)*. Let us define:

$$f(\cdot) = f\left(s, e, p\right) \qquad (1)$$

$$g(\cdot) = g\left(w(p), b(p), c(p), r\right) \qquad (2)$$

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 specific factor (r) that takes into account 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 a researcher is to a densely populated network of public and private organisations the lower will be her search costs as she will be well informed about available positions. The extend of one's social network, hence, increases the researcher's probability of receiving an offer *f(.)*. The probability of receiving a job offer *f(.)* also depends on environmental labour market characteristics (*e*) such as the existence of a strong potential demand. Potential demand in terms of flexibility and thickness of the academic market is scientific field, country and time dependent. The researcher's personal characteristics (*p)* (such as PhD granting institution, tenure, past publications), which could be interpreted as signalling high individual productivity, positively affect the probability of receiving a job offer *f(.)*.

The probability of accepting an offer *g(.)* depends on the salary offered (*w*), the retention strategy of the university that can offer an increase in the salary (*b)* and the mobility costs (*c)* and all of these factors are affected by researcher's personal characteristics (*p).* A key determinant of the probability of accepting a job offer is the academic position of the researcher. Non-tenured researchers are more likely to accept an offer than tenured university staff as they do have non-zero probability of having a non-renewal of contract (all non-tenured positions are based on "soft" money that is time limited). The higher the academic's position and her experience in that position, the higher will be the salary in her current university. However, academic salaries tend to vary within a well defined national ladder based on experience with some limited flexibility at the top depending on the country. In the US and less so in the UK professorial salaries can vary significantly, however, in most other countries public employee contracts or tradition give little space for salary increases. This will lead in the academic labour market to a reduced effect of the salary on the probability of moving.

The probability of accepting an offer *g(.)* depends negatively on mobility costs (*c)*. Mobility costs include direct personal costs of moving to another city or country and skill adjustment costs that are particularly important for high skilled jobs. If the researcher's skills are university specific (i.e. not all the routines of the academic teaching and research work will be transferable to the work in the new university and even more so for a move to a firm), she must learn new practices, protocols, routines and adjust to different management and administration procedures. Thus, a period of adjustment with lower expected efficiency may be required. Even if these skill adjustments are minor, they can be considered as sunk costs and could deter some researchers from moving.[6] This is especially true for mature academic researchers, who have invested a lot of time in accumulating the skills and reputation needed to succeed in a specific university environment. Both direct and skill adjustment mobility costs are decreasing in the number of times a researcher has moved due to learning effects. Finally, personal characteristics *(p)* (such as age) can affect the probability of accepting an offer due to family related consideration that can both increase or decrease mobility costs.

Past research performance is one of the personal characteristics *(p)* affecting directly the probability of receiving *f(.)* and indirectly of accepting a job offer *g(.)*. Researchers with a good publication track record will have better career and retention package prospects; increasing *(b)* and affecting *g(.)*. However, academic researchers who have more fertile ideas (are more productive) have a higher chance of receiving a job offer from another university as research performance is usually considered the most important criteria for selection (a conditio sine qua non). Previous research performance can be seen as signalling a high quality researcher, increasing both the probability of receiving an offer *f(.)* and the salary being offered *(w).* At the same time, according to the discussion in the previous section, the probability of accepting an offer *g(.)* also depends on the expected higher research performance *(r)* that the researcher can achieve in the new job at a higher rank institution.

We can think of a reverse causality from mobility to productivity. A change of job can have an impact on the research performance of a scientist after her move to the new one. The short to medium term (let us say a 3 to 7 year window after the change) post-mobility productivity of the

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

researcher is affected by her reasons to move. We can elaborate that 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 can happen because of better salary (*w)* and other 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 we could expect a positive impact on the productivity of the researcher. Hence, not all types of mobility are associated with increased research productivity.

In the basic job search model the difference V_{t+1} - V_t should be higher than mobility costs (*c)* for a job change to happen. Mobility costs are assumed to be instantaneous. However, mobility can be associated with significant deferred adjustment costs that can have a negative impact on the post-mobility productivity as the researcher will have less time to spend on research activities due to the need to spend more time on learning tasks that could have been done more efficiently in her previous job due to knowledge of practices, protocols and routines (Shaw, 1987; Groysberg, 2008). Following the job change the researcher therefore witnesses a period of decreased productivity also associated with the setting up of the new laboratory in lab-based sciences. The length of the period and depth of the reduced productivity depends on the relevance of the adjustment costs, which in turn depend on the learning required to adjust to the new job. Job changes can therefore be associated with no change in the short to medium term scientific productivity if the reasons for moving are exclusively related to traditional job search factors and to a positive increase if mobility is driven by research and reputation reasons *(r)*. In both cases we can expect a decrease in productivity due to adjustment costs in the short run.

But why should one expect a positive impact on productivity of the move to a better research and reputation environment? Two approaches can be framed here. The first is based on the matching model idea, the second on the increase in human (more diverse opportunities of learning) and social (better network connections) capital through mobility. The matching model predicts that researchers with high potential productivity unexploited in a lower quality department move to a higher quality department, where they can find better endowed laboratories (better equipment and more junior research staff) and hence increase their productivity. Second, a move to a better department means a move to a better research group with positive peer and network effects that increase the productivity of the researcher. 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 better communication technology (see also

Ding et al. (2009)). Working in a department with high quality peers does not only enhance productivity through direct interactions, but also through privileged access to their social network. Moreover, mobile researchers benefit from their existing network, which they carry into the new environment (Azoulay et al., 2010; Waldinger, 2010) creating new extended networks with the potential for new combinations. It is very difficult to disentangle the matching effect from the social/human capital model as in a highly reputable department the two are present (funding for good labs and high rank peers that allow the access to better social network and better learning). Moreover, highly reputable researchers tend to concentrate in highly ranked departments (Oyer, 2007) as they are the source of the ranking and due to a competitively based allocation of resources they are also the departments that receive most funding.

Within this framework, we hypothesise that only a move to an institution of higher quality/reputation will be associated with a medium term increase in productivity; after an initial period in which adjustment costs may constrain the productivity increase we should expect an increased research performance. If we think that scientific production is strongly affected by cumulativeness and self-reinforcement phenomena (Dasgupta and David, 1994), we could expect that an improvement in medium term productivity will be persistent and thus will affect the long term performance of researchers. Conversely, mobility to an institution of the same or lower quality/reputation level should be associated with a short term productivity decrease due to adjustment costs that can only be slightly mitigated and at best stabilized to pre-mobility (for same rank change) or lower levels of productivity in the medium to long term due to a deficiency in financial and human resources assuming that the move is associated with a similar work profile (e.g. similar teaching and administration load).[7]

The impact of job changes on scientific productivity is mediated by the interaction between mobility and career development. It is possible that the relationship between mobility and researchers' productivity not only changes across different types of mobility (to higher or lower quality institution) but also across the career cycle. Moreover, there may be a trade-off between career progression and quality/reputation of the institution. These relationships are important to qualify the impact of mobility on researchers' performance.

Mobility at different levels of the career (UK: lecturer, senior lecturer/reader, full professor) could result in differences in productivity growth. Mobility could have a higher impact on research

[7] Relaxing this assumption would mean to consider either the case in which the work load would diminish (I move to a department of lower reputation but were I have to teach less as there I am considered a star) resulting in a positive impact on scientific productivity or the case of a move to a more teaching intensive institution (for example in the case in which I did not get tenure/permanent contract in a top department) resulting in a decrease in productivity.

performance in the early phase of a researcher's career when highest quality research is realized (Zuckerman & Merton, 1973). Mobility in early career stages would enable researchers with unexploited productivity potential to perform at their best in a higher ranked institution having a major impact on their future performance due to the cumulative characteristic of knowledge production.

Career progression may also have an impact on researchers' productivity as, especially in the case of promotion to full professor, career steps are associated with access to more resources and larger labs resulting in higher productivity (Long & McGinnis, 1981). A researcher may choose to move to an institution of the lower quality/reputation but in a higher career position and thereby counterbalancing the null or negative effect of downward mobility with the positive bust given through career progression. This is particularly true in the case of strategic hiring by lower ranked institutions that might offer attractive professorship positions, usually in term of salary but also in terms of teaching duties and research support, to highly qualified middle level researcher from higher ranked institutions. We further hypothesise, that a move to a higher ranked institution in a higher career position is unlikely to be achieved. Oyer (2007) confirmed for a sample of US tenured economists that the chance of an external researcher to be offered a position in a different department is lower than for a local, immobile researcher to received tenure. Similarly, Chan et al. (2002) find that very few researchers are able to move to a higher ranked institution and that these few exceptional scientists are two times more productive than the average academic at the destination university. Thus, we can expect a better match between a talented researcher coming from a lower quality department and her new research environment resulting in a combined effect of increased access to resources and a higher ability to exploit these resources than someone hired without career promotion.

We recognize that a dynamic perspective of researchers' mobility is necessary. This would imply not seeing researchers' mobility as a one-step process but taking into account the short and long term return opportunities. Successive changes in job positions associated or not with career advancement, in/from higher rank institutions should be considered in order to assess possible return opportunities. However, the data required to estimate such a model is not currently available. This paper is just a first step in. In the next section we present our data and, constrained by the data characteristics, the estimation model chosen. We focus on the short to medium term impact of mobility on scientific productivity of researchers providing a first attempt to test some of the predictions linked to institutional quality/reputation, controlling for a limited, but important, subset of qualifying characteristics of researchers' mobility such as career progression.

3. Empirical Analysis

3.1 The Sample

The empirical study is based on a sample of 171 university researchers working at 45 UK academic institutions in 2005 and in four scientific fields: chemistry, physics, computer sciences and mechanical, aeronautical & manufacturing engineering.[8] For the purposes of this study, career information taken from CVs was codified in order to construct comprehensive profiles of researchers spanning their career from PhD award through to 2005, which resulted in a panel with 3551 observations.

CV data has been found to be very useful in the analysis of academic careers as it informs about job transitions and additionally allows for the gathering of reliable publication data (Cañibano & Bozeman, 2009). Using data collected from CVs in addition to the ISI Web of Science (WoS) improves accuracy of the data as mismatches arising from name similarities and changes in researchers' institutional affiliations can be avoided. CVs of researchers included career path information and allowed us to identify 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 job change in the same university to a higher position). We also only consider changes that occur after the researcher received her first "tenure-track" position in academia or first full time position in industry after her PhD[9]. We hence limited the analysis of the influence of job mobility on researchers' productivity in this paper to either tenured or tenure-track equivalent positions. Accordingly, postdoctoral research positions are not considered real labour mobility in our analysis.[10] For the UK 'lecturer' and 'research fellow' positions can be considered the minimum tenure-track positions in academia, followed by 'senior lecturer', 'reader' and 'professor'. Research fellow positions are only considered if they exceed a

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

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

[10] "Postdoctoral mobility" and "job mobility" have very different patterns (Zubieta, 2009). Post-doctoral positions may also include research fellowship positions. As the contractual relationship of these types of positions was not always clearly specify in the CVs, it was difficult to distinguish research fellowships from post-doctoral stays. In addition, the increasing number and successive post-doctoral and temporal positions prevent us from considering post-doctoral research stays as real labour mobility, as we try to "qualify" job changes. For the same reason, we do not consider collaborations as real labour mobility.

period of four years and represent independent research, i.e. are not under the direct supervision of a professor. Academics in the UK are usually hired on permanent contracts, which, in the case of lecturer appointments or research fellowships, are subject to a probation period of three years. . Thus, mobility in our sample is likely to be voluntary, where researchers leave a permanent position for reasons other than termination of contract.

The sample consists of researchers who were active in 2005 aged 29 to 77. The mean age of our 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 three to 49 years, with an average observation period of 20 years. In our sample of 171 UK academics, 145 (85%) start their career as lecturer or research fellow; 22 researchers (13%) take up their first position in industry and two researchers start in senior academic positions (Figure 3). For two researchers first positions were not evident from the CVs. The mean starting age is 28.6 with a minimum of 22 years and a maximum of 38 years (Figure 4). [11] The mean PhD age is slightly lower with 27.2. A total of 45.2% of researchers take up their first position right after PhD award, while 35.5% undertake short post-doctoral stays of up to 3 years and 13.3% take up postdoctoral research for up to 7 years. 6% of researchers in our sample started their working career while or before studying for their PhD.

CV information further allowed us to assign publications from the Web of Science to each researcher. Academics in our sample published an average of 4.35 publications per year between 1982 and 2005. A total of 94 researchers (55%) publish their first article before taking up their first tenured employment, during their PhD or post-doctoral appointments. The average number of publications per researcher per year increases from an average of 3.9 in 1982 to 4.63 in 2005 (Figure 5). This increase could partly be due to life-cycle effects, year effects or mobility effects, which this paper attempts to measure.

3.2 Mobility, productivity and quality/reputation of the institution

The UK academic market differs from that of the rest of Europe. It is characterised by its internationality, attracting academics from across the world, and by competition amongst universities for the most promising scholars (BIS, 2011; Ziman, 1991). Further, the four-step promotion system and race for positions at the most prestigious institutions (Hoare, 1994) make the UK system more competitive than other academic markets in Europe. There is no obligation to

[11] Researchers joining the sample at a later age may have pre-PhD experience in academia or industry; however, this is not recorded in our data.

move after PhD completion, however, mobility barriers are very low and mobility is usually rewarded, making the UK academic labour market very fluid.

In our sample, 109 researchers (64%) change 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 one person changing four times. The mean number of years in one job is 10 years. Our analysis will be limited to job changes that occur between 1982 and 2005 to allow for an adequate number of researchers in each observation period and because some of the explanatory variables are not available for earlier years. In 1982 the number of observed academics is 60, increasing to 171 in 2005. We record 126 job changes by 97 researchers between 1982 and 2005. Of these, 67 are job changes between UK higher education institutions.

In the theoretical part of this paper, we stressed that research and reputational factors are crucial in explaining the academic labour market. Access to resources and a better research environment provide incentives to move and are fundamental when analysing the impact of mobility on scientific productivity. Wages play a less important role in the academic labour markets and are of less concern explaining job changes, especially considering the high level of standardisation of academic salary scales. Therefore, we identify job changes to either a higher or lower quality/reputation institution. To measure esteem or prestige of universities we use the quality-weighted number of publications published by the respective organisation on WoS during the years *t, t-1* and *t-2*. Quality or reputation is measured as a three-year moving average to smooth the distribution and was calculated for all the years 1982 to 2005. Publication counts are calculated separately for two main subject categories: (1) natural sciences and (2) engineering sciences and weighted by the average number of citations per paper divided by the average citation count for publications in the respective subject area and year.[12] Quality-weighted publication numbers should give a good picture of both the quality and the research size of a department. The measure was calculated for UK universities only and we thus have to exclude international mobility from the analysis. Researchers in our sample work at 53 different UK universities between 1982 and 2005, and 56 researchers move 67 times between these universities. Of the 53 UK universities present in the sample 47 belong to the top 50% in their field and 17 universities belong to the top 10% in the field of engineering and science. Upward mobility is defined as a move to a department producing at least 25% more quality-weighted publications than the prior department, and downward mobility as a move to a department producing at least 25% fewer quality-weighted publications. In our

[12] The data has been compiled by Evidence, Thomson Reuters.

sample, 25 academics are able to move 27 times to a more prestigious institution, while 29 researchers move 29 times to less esteemed institutions between 1982 and 2005.

Figure 6 shows the mean number of publications for the 12 years surrounding a move. We plot the graph for all 67 moves between UK universities as well as separately for 27 cases of upward and 29 cases of downward mobility. We can expect publications to result from research undertaken the previous year. Thus, articles published in the year of the move would still reflect research undertaken at the previous institutions. Job mobility is generally followed by a decrease in publications in the year following the move. This reflects costs of mobility and adjustment, which most likely resulted in a decrease in research efficiency in year *t*. The number of publications, however, increases from year two on. For downward mobility the rate of publications does not improve but stays largely the same. For upward mobile researchers the number of publications is slightly higher than for other types of mobility already before the year of mobility. The mean number of publications increases further after the move. Hence, academics moving upwards are already performing above average before the move while downward mobile academics have below average performance and are not able to benefit from a job move. The difference between the two becomes even more prominent. The graph is consistent with results found by Alison and Long (1990), but in contrast to their results the upward mobile group already starts out with higher productivity than the downward mobile group.

In the theoretical part of this paper we have discussed the interaction between the impact of upward and downward mobility on productivity and career progression. We measure career progression as advancement in academic rank from Lecturer to Senior Lecturer/Reader to Professor. Promotion information was only available for 150 academics; we thus had to reduce our sample size. We observe 138 promotions of 105 academics between 1982 and 2005, 70 first career promotions (research fellow/lecturer to lecturer/senior lecturer) and 68 promotions to professor. On average, academics are 36 years old when being promoted for the first time, though the minimum promotion age is 28. The average age at promotion to professor is 45 with a minimum of 31 and a maximum of 69. Thus, on average, academics are promoted for the first time 7 years after taking up their first position and advance to professor 18 years after their initial appointment.

A total of 43 promotions are accompanied by a job move (47% of all academic job moves), 29 of which are first career promotions and 14 are promotions to professor. The number of career moves between UK universities is 35. While 50% of academic job moves in the UK are accompanied by career progression, this mainly affects downward mobility (67% of downward moves, 35% of upward moves). Still, researchers that gain promotion through mobility are a minority. Only 31% of promotions are gained at a new institution. The vast majority of academics are promoted in their home institution. However, those that move to be promoted are on average promoted much earlier than their peers. Their average age for first promotion is 34.5 (1.5 years earlier than those that do not move) and the average age for promotion to professor is just 39 (6 years earlier)

3.3. Other mobility specifications

Mobility from Business

Several authors in the sociology of science have investigated the consequences of mobility between an academic and a business environment, focusing on the problem of adaptation due to different norms and patterns of behaviour, such as a higher level of secrecy required in the business world, which can affect post-mobility productivity (Marcson, 1960; Krohn, 1961; Kornhauser, 1962; Hagstrom, 1965). The literature has focused on the move from academia to industry without considering mobility back into academia. Researchers can spend part of their career in industrial laboratories and then return to universities (Dietz and Bozeman, 2005).

It has been argued that movements to other sectors increase researchers' human and social capital and may have a positive effect on productivity. Dietz & Bozeman (2005) indeed find a positive effect of years spent outside academia on patent productivity. However, mobility to a company can refocus a researcher's work to more applied matters that are more relevant to the company and may also discourage publications. This in turn may lead to a reduced accumulation of human capital for the researcher that can negatively affect her subsequent scientific performance (Cotgrove and Box, 1970).

This interpretation, however, could be distorted by the simple fact that in certain scientific fields (such as aerospace engineering) company laboratories are better equipped than the majority of university laboratories. A move from a lower rank university to a company laboratory followed by a return to a university could thus result in an increase in the productivity of researchers consistent with the matching model presented above. Conversely, a move from a less well-equipped laboratory back to academia could decrease the publication record of a researcher as we can assume that the adaptation cost of such a researcher is higher than that of a researcher moving within academia.

We are able to consider mobility from industry to academia and vice versa in our sample. A total of 28 researchers (16%) move from industry to academia between 1982 and 2005. Five researchers leave academia during this period, though they return to university appointments by 2003 (our sample includes only researchers working in academia in 2005). The majority of industry hires join academia as senior lecturer/reader. Only five researchers are appointed to professorships upon their entry to academia. Most academics working in industry did so in highly prestigious industry laboratories (e.g. AEA, GEC, ICI) in their function as senior researchers. Almost 50% are later joining physics departments, while only three industry researchers join chemistry.

3.4 Econometric Specification

Mobility is measured as job changes between different academic institutions in the UK. Changes between different universities can be accompanied by a change to a higher or lower ranked university. Our specifications consider job changes of a researcher in a tenured position and aim to measure their impact on individual productivity.

Specification (1) assumes a positive career effect of mobility and models it as an indicator variable. It aims to analyse post-mobility productivity and includes several lags of our mobility indicator in the analysis. We consider time-windows of 3, and 6 years after job transition:

$$\mathrm{PUB}_{\mathrm{it}} = \alpha + \sum_{k=1}^{l} \beta_{\mathrm{k}} MOB_{it-k} + \chi \mathrm{x}_{\mathrm{it}} + \partial \mathrm{w}_{\mathrm{i}} + \mu_{\mathrm{i}} + \upsilon_{\mathrm{it}} \tag{1}$$

where Pub_{it} is the number of publications by researcher i in year t, Mob_{it-k} is an indicator for job transition, x_{it} represents other time-varying individual characteristics and w_i observed time-invariant characteristics of researcher i. μ_i indicates the unobserved individual effect and v_{it} the error term. l represents the number of lags used in the specification (3 or 6).

Specification (2) considers different mobility characteristics, e.g. upward mobility and downward mobility.

$$\mathrm{PUB}_{\mathrm{it}} = \alpha + \sum_{k=1}^{l} \beta_{\mathrm{k}} MobilityType_{it-k} + \gamma_k MobilityType_{it-k} \times Promotion_{it-k} + \chi \mathrm{x}_{\mathrm{it}} + \partial \mathrm{w}_{\mathrm{i}} + \mu_{\mathrm{i}} + \upsilon_{\mathrm{it}} \tag{2}$$

where $MobilityType_{it+k}$ indicates the nature of job transitions: i.e. a change to a more esteemed-institution or a change to a less prestigious institution and is interacted with a variable $Promotion_{it+k}$ that controls for a potential differential effect for moves that are accompanied by a promotion to a higher rank.

We assume the number of publications to have a Poisson distribution and to be overdispersed. To account for overdispersion as well as unobserved heterogeneity among academics we assume a negative-binomial distribution.

We control for individual heterogeneity by specifying the average productivity of the academic before she enters the sample. The pre-sample mean of the dependent variable has been shown to be a consistent estimator of the unobserved individual heterogeneity (Blundell et al., 1995). Individual heterogeneity mainly corresponds to the intrinsic ability of an academic and her motivation, both factors that are not directly observable but may affect scientific productivity. The average number of publications published before the academic enters the sample (before she arrived in her first position or before 1982) should capture these individual characteristics and can serve as a fixed effect proxy that helps solve the problem of unobserved individual heterogeneity.[13]

In our sample we assume that we only observe voluntary mobility. The literature suggests that more productive researchers have many more opportunities to change their jobs. Thus, endogeneity arises as a position is only offered to the most productive academics. The fixed effect proxy containing pre-sample data on publications helps to address the problem of endogenity that arises from unobserved heterogeneity across individuals which may explain both, productivity and mobility.

Academics may further move due to lack of opportunities in their home institution and the prospect of promotion in a new institution. Academic promotion is closely related to productivity itself with the most productive individuals being promoted quicker, and senior researchers being offered more opportunities to increase their productivity. It is therefore important to consider promotion and academic rank when measuring the relationship between mobility and productivity. As publications represent research undertaken in the year prior to its publication they may also effect promotion and mobility in *t*. We will therefore use lags of potentially endogenous explanatory variables like mobility and academic rank to control for some of this contemporaneous endogeneity caused by reverse causality. We further examined this problem by running a SUR estimation (running the mobility and productivity regressions simultaneously). The results, however, showed that the standard errors are independent and that there is no need for a simultaneous equation, i.e the two processes do not happen simultaneously.

3.5 Variables

Our primary objective is to measure the effect of job mobility on research productivity in terms of publication numbers controlling for career patterns and mobility to business. The dependent variable in all our specifications is the number of publications in year t (PUB_{it}).

[13] Alternatively fixed individual effects could be included to control for unobserved heterogeneity, however, this approach does not allow us to include some of our controls and is hence not found appropriate for this analysis.

Mobility is measured as a binary variable that equals one in the year of job transition *($MOB_{i,t-k}$)*. Our main focus is on mobility between universities and we therefore estimate the same model focussing on moves between UK higher education institutions ($UNIMOB_{i,t-k}$). Mobility differs in nature and we therefore use measures for mobility relating to the nature of the transition: (1) *Upward Mobility ($MOVEUP_{i,t-k}$)* defining a move to a university of higher esteem, and (2) *Downward mobility ($MOVEDOWN_{i,t-k}$)* defining a move to a university of lower esteem.

As controls we use the academic's age[14] (AGE_{it}) to account for potential life-cycle effects (Levin and Stephan, 1991). Additionally, we consider the gender of the researcher ($MALE_i$). Further, we control for the academic rank of a researcher. The UK university system requires researchers to fulfil minimum requirements to be considered for promotion. Thus, academics in lower ranks should have more incentives to publish. Professors on the other hand have access to research assistance and funding that may allow higher rates of publications. We hence consider three "ranks" in our analysis: Lecturer or Research Fellow before first promotion ($RANK\ 1_{it-1}$), senior position or rank after first promotion ($RANK\ 2_{it-1}$), and professorship ($RANK\ 3_{it-1}$). Researchers that are employed in industry are not subject to academic promotion. We therefore include a firm dummy that indicates whether a researcher is working in industry ($FIRM_{it-1}$). All indicators are lagged by one period to account for some of the endogeneity caused by reverse causality. To not only account for current employment in a firm but for industry experience we additionally include a variable that indicates whether a researcher currently working in academia has worked in industry before ($INDEXP_{it-1}$). We further consider indicators for postdoctoral research activity ($POSTDOC_i$). To control for discipline effects we include subject dummies to the regression ($DISCIPLINE_i$).We also include year fixed effects in all regressions.

To address the issue of industry experience with regard to mobility as discussed above we introduce an additional regression that considers *from Industry mobility ($INDMOVE_{i,t-k}$)*, which measures a transition from industry back into academia.[15] A summary of all variables and their descriptive statistics can be found in Table 1.

4. Results

We estimate the model described above as a negative binomial regression. Standard errors are clustered at the individual level and robust to heteroskedasticity and serial correlation. Tables 2, 3, 4

[14] Age was only available for 170 of our 171 researchers.

[15] Mobility from Academia to Industry only occurs 5 times in our data and is therefore not considered at this occasion.

and 5 show the results for 3 and 6-year lags of the different mobility variables respectively. The number of researchers in our dataset is reduced to 147 in column 1 of Table 2 due to missing values in some of the variables and short observation periods for some academics. In column 2 the number of researchers is reduced to 130 due to deeper lags that require a minimum of 7 observation years, hence only considers academics that start their career before 2000. In column three we repeat the regression with three year lags on the reduced sample of 130 academics to control for any potential sample bias. Given changes in the sample, we can only consider robust results those that remain constant across the three specifications. Columns 4 to 6 only consider mobility between UK universities. We exclude all researchers that moved internationally or to industry as they might introduce a potential bias (i.e. they may appear immobile).[16]

The coefficients for non-mobility variables are consistent across the different mobility measures and lags. We report their results from the first specification in Table 2, which represents the largest number of observations. We used pre-sample information on publication numbers to proxy for unobserved heterogeneity. The pre-sample proxy is positive and significant. However, we cannot rule out that some unobserved heterogeneity remains.

Several individual factors are associated with productivity. Age is positively correlated with publication numbers, but this effect is not significant. We also included a quadratic term in our regression, which seems to suggest a decrease in productivity over the life-cycle, however, it is not statistically significant. We also do not find a significant gender effect. We find evidence for an increase in publications along academic ranks. Senior academic staff are expected to publish 1.3 (=exp(0.241)) times more than researchers in the reference category *RANK 1*; professors are expected to publish most. For example, a male junior academic, who has no industry experience, no postdoc and has not been mobile in the last three years, is expected to publish 3.11 publications in an average year (more than one publication less than the sample mean)[17]. A professor with a similar profile publishes 4.01 publications in an average year. This result might partly be driven by the subject areas we are considering, which are largely organised in labs headed by a professor.

We find a negative effect for researchers that worked in industry in the previous year. Their publication rate would be 0.7 times lower than that of a university lecturer or 2 times lower than that of a professor, producing just two publications per year. Further, we find a negative, albeit

[16] The results are robust even if we include the whole sample.
[17] Margins calculated at the mean age and for balanced data distribution across the four scientific fields. Disciplines with higher levels of publications (chemistry and physics) are more frequent and therefore marginal predictions of the observed data would return larger predicted publication counts (4.49 and 5.86 for lecturers and professors respectively).

insignificant effect for academic researchers that have worked in industry in the past. Past employment in industry hence has a negative impact, if any, on current publication rates.

We further find that a post-doctoral research stay does not improve future publication numbers. In fact a post-doctoral appointment of more than three years has a negative effect and decreases publication rates by a factor of 0.7 to just 2.6 publications per year[18]. Researchers securing an independent position straight after their PhD hence seem to perform better, a result that may be driven by our conceptualisation of post-doctoral, untenured positions as any research only position of less than five years.

Looking at academic disciplines, we see that researchers in Chemistry publish significantly more than their colleagues in other fields (predicted number of 6.02 publications), with Computer Sciences producing least publications (margin of 1.49 publications)[19]. [20]

4.1 Mobility and quality/reputation of the department

Coefficient estimates show that once controlling for intrinsic ability, age, academic fields and years, mobility has no significant effect on productivity in the short run. Using 6-year lags of mobility in columns 2 and 5 instead of 3-year lags does not change this. However, we can observe a tendency from an initial negative effect towards a positive coefficient in later years, especially for inter-university mobility.

The mobility effect is conditioned by the nature of job transition in Tables 3 and 4. Columns 1 to 3 in Table 3 report the results for upward mobility (*MOVEUP*). They show that upward mobility has a larger positive coefficient from year two onwards than mobility in general. This positive effect turns significant, in later years. We also observe an initial drop in productivity in year one following the move indicating some kind of mobility cost that reduces publications initially but increases them in the medium term.

Columns 4 to 6 of Table 3 report the results for downward mobility (*MOVEDOWN*). They show that a move to a university of lower rank does indeed decrease the number of publications in the following years. This negative effect does not diminish over the years and also after six years, we

[18] Margins calculated as before with balanced data distribution across fields and observed data distribution for academic ranks and years.

[19] Margins calculated for male researchers that have been immobile in the past three years, at average age and observed data distribution across academic rank, post-doc experience and industry experience.

[20] We include year fixed effects in all regressions. In the UK the Research Assessment Exercises (RAEs), which will be replaced by the Research Excellence Framework (REF) in 2014, have caused stronger pressure on academics to publish more in the years preceding the assessment. We therefore pay particular attention to the effect of the 1995 and 2000 year dummies, the years that marked submission dates for the RAEs and should thus be accompanied by a higher number of publications. We find no significant year effect on publication numbers showing that while the RAE may affect the choice of publication outlet or guide hiring decisions, it has no effect on the number of publications.

still find that the expected number of publications for a researcher that has moved to a university of lower prestige is lower than the expected number of publications for other researchers. The negative effect is only significant for years three and four of our regression, possibly due to the low number of downward moves.

While the positive effect of upward mobility and the negative effect of downward mobility previously observed in the descriptive statistics could not be definitely confirmed in the regression, we find some evidence supporting the validity of our hypotheses.

In Table 4 we introduce an interaction term to take into account the relationships between academic promotion and mobility. We earlier hypnotized that mobility that is accompanied by promotion to a better position will result in an increase in publications also for downward mobility due to better access to resources associated with an increase in rank. The results in columns 1 to 3 show that for upward mobility the positive effect, observed in Table 3, is indeed driven by researchers that are promoted at the time of the move. While we find a negative insignificant effect for upward mobility in general, the interaction terms are positive significant, indicating that those researchers that move due to promotion opportunities publish significantly more articles than researchers that move without promotion. The effects are not jointly significant (standard *t-test* for joint significance), as seen in Table 3, however, in an estimation that only measures the effect of promotion mobility we would see a positive significant effect from year three onwards.

In columns 4 to 6 we report the results for downward mobility and its promotion interaction terms. The main effect is negative but insignificant, in accordance with results in Table 3. The interaction terms are also negative, but only significant in years three and six. Thus, while the differential effect of downward mobility with promotion on productivity is not significantly different from downward mobility that is not accompanied by promotion, both indicate a negative effect on publication outcome. Thus, our hypothesis that downward mobility to a better position may enable access to better resources and result in an increase in publication numbers is not confirmed.

<u>Robustness check</u>

It is interesting to further analyse if a move to one of the top 10-percentile science or engineering departments in the UK has a stronger effect on publication rates than upward mobility in general. The 90-percentile represents a reduced but significant sample of top-universities that stand out from our overall sample. The literature has not identified any relevant hypotheses considering mobility in and out of this top group. One could expect that moving to the top institutions would provide a boost to a researcher’s performance; however, top departments can be very challenging places due to intense competition among colleagues that can result in a less productive environment for a researcher coming from a lower ranked institution. For this purpose we classified university departments as belonging to the 90-percentile of departments in its field in the UK in a given year based on our quality weighted productivity measures. Of the 25 institutions that are ranked amongst the top 10 at least once during the observation period, 17 are represented in our sample. In total, 104 researchers work at one of these top departments for at least parts of their career. This represents almost 70% of our sample and shows that the majority of scientists are working at established, excellent departments. However, we observe some mobility to and from this group of top-departments and 97 researchers (65% of the sample) spend at least parts of their career outside the 90-percentile. We then differentiate between mobility from the top group to a university outside the top-group (19 moves), mobility to a different university in the top group (15 moves) and from a low ranked university to one of the top 10-percentile departments (16 moves). Figure 7 shows the productivity pattern for moves to one of the top 10-percentile departments and moves away from one of these top departments. The graph indicates that productivity is already declining before an anticipated move for researchers that eventually move downwards. Conversely, researchers that go on to a top-university already increase their productivity throughout the years preceding the move. This graph contradicts results by Alison and Long (1990), who argued that productivity is mainly driven by department quality, but confirms finding of Oyer (2008) and Chan et al. (2002) that only the most productive researchers are able to move up. Table 5 reports the results for the three mobility groups for lags of 3, 6, and 3 years in a reduced sample respectively. The results show that a move to a top department is associated with a negative effect in the short term (significant in year one) that turns into a positive and significant effect in year six, indicating that there might be some long term benefits to joining a top department. Non-upward mobility shows always negative though insignificant coefficients.

4.2 Inter-sector mobility

Table 6 reports the results for mobility from industry to academia. The regressions include all researchers, also those that were mobile between universities. Researchers that join academia from industry (*INDMOVE*) publish less than their peers during the first two years after the move. Column 2 shows that that this initial negative effect turns positive in year three. Thus, while industry researchers may suffer some adaptation costs when joining academia, they benefit from their presumably increased human capital acquired during their time in industry and publish more in the medium term.

5. Discussion and Conclusions

This article analyses the impact of mobility on researchers' productivity. We address the relationship by developing a theoretical framework based on the job-matching approach for academics and the idea of productivity being driven by capital availability and peer effects. We consider job changes qualifying them in term of upward and downward mobility, career promotion, mobility from business and international mobility.

The empirical analysis is based on the entire careers of a sample of 171 UK academic researchers, spanning from 1957 to 2005. Based on this sample, that should not be biased in relation to mobility, we discovered a very high level of job mobility, two third the researchers changed job at least once and one third twice. In this respect, the UK academic labour market looks much more like the US system rather than other European systems. We analyse the impact of job changes on the post mobility output in 3, and 6 year periods. Contrary to common wisdom, we do not find evidence that mobility per se increases academic performance. Mobility to better departments has a positive but weakly significant impact while downward mobility results in decreasing researchers' productivity. Mobility associated with promotion tends to result in an increase of productivity as mobility from industry to academia but only after an initial negative effect.

These results should be taken with a certain amount of caution due to the small number of observations used. Though mobility is very widespread in the UK science system it was very difficult to build a complete career dataset for a large sample of researchers which such an analysis would require. Thus we were not able to develop more complex econometric models that could take into account interactions amongst the various determinants. We must also acknowledge that, though we use a dynamic model lagging possibly endogenous variables, our results may be biased due to the omitted variable and reverse causality problems. As discussed in Section 2, mobility is driven by research performance and opportunities, which create reverse causality that may potentially bias our results. We are currently exploring estimations based on selection and instrumental variable approaches to tackle this potential endogeneity.

Though this study provides only preliminary results for a small sample of UK researchers, we think that we provide interesting new original evidence about mobility that challenges what is commonly accepted in the policy arena, i.e. that mobility is beneficial and should be encouraged. Our results point to a complex interaction between mobility and productivity that only in certain specific circumstances result in a positive impact of the former on the latter. The results suggest the need for much more fine tuned policies for mobility of researchers. At least in terms of the expected impact on productivity, mobility is not always beneficial for individual researchers. Instead, mobility is always associated with a short-term decrease in productivity due to the adjustment costs and only under certain circumstances does it results in an increase in productivity. In this paper we did not aim to assess either the long term impact of mobility or its societal effect. Mobility may not always be good for the individual researcher but it could be positive for the science system as it helps the diffusion of ideas.

References

Allison, P.D. and Long, J.S. (1987). Interuniversity mobility of academic scientists. *American Sociological Review*, 52, 643-652.

Alison, P.D. and Long, J.S. (1990) Departmental Effects on scientific productivity. *American Sociological Review*, 55 (4), 469-478.

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

BIS (2011) International comparative performance of the UK research base – 2011. Elsevier: http://www.bis.gov.uk/policies/science/science-innovation-analysis/uk-research-base.

Blundell, R., Griffith, R. and Van Reenen, J. (1995) Dynamic count data models of technological innovation. *Economic Journal, Royal Economic Society*, 105 (429), 333-44.

Cañibano, C. and Bozeman, B. (2009) Curriculum vitae method in science policy and research evaluation: the state-of-the-art. *Research Evaluation*, 18 (2), 86–94.

Chan, K.C., Chen, C.R., Steiner, T.L. (2002) Production in the Finance Literature, Institutional Reputation, and Labor Mobility in Academia: A Global Perspective. Financial Management, 31, 131-156.

Cooper, D.P. (2001) Innovation and reciprocal externalities: information transmission via job mobility. *Journal of Economic Behaviour and Organization*, 45, 403-425.

Cotgrove, S. and Box, S. (1970) *Science, industry and society*. George Allenand Unwin

Crespi, A.G., Geuna, A. and Nesta, J.J.L. (2007) The mobility of university inventors in Europe. *Journal of Technology Transfer*, 32, 195-215.

Crespi, G., D'Este, P., Fontana, R. and Geuna, A. (2011) The impact of academic patenting on university research and its Transfer. *Research Policy*, 40, 55-86.

CST, Council for Science and Technology (2010). A vision for UK research. London.

Dasgupta, P. and David, P.A. (1994) Toward a new economics of science. *Research Policy*, 23 (5), 487-521.

Dietz, J.S. and Bozeman, B. (2005) Academic careers, patents, and productivity: industry experience as scientific and technical human capital. *Research Policy*, 34, 349-367.

Ding, W.W., Levin, S.G., Stephan, P.E. and Winkler, A.E. (2009 The impact of information technology on scientists' productivity, Quality and Collaboration Patterns. *NBER Working Paper* No. w15285.

European Commission (2001) High-level Expert Group on Improving Mobility of Researchers. Final report: Brussels.

European Commission (2006) Mobility of researchers between academia and industry. Brussels.

European Commission (2010) Communication from the Commission "Europe 2020 Flagship Initiative Innovation Union" SEC(2010) 1161.

Elton, L. (2000) The UK research assessment exercise: unintended consequences. *Higher Education Quarterly*, 54 (3), 274 - 283.

Groysberg, B. (2008) How star women build portable skills. *Harvard Business Review*, 86, 74-81.

Hagstrom, W.O. (1965) *The scientific community*. New York: Basic Books.

Hargens, L.L. and Farr, G.M. (1973) An examination of recent hypotheses about institutional inbreeding. *American Journal of Sociology*, 78, 1381–1402.

Jovanovic, B. (1979) Job matching and the theory of turnover. *The Journal of Political Economy*, 87 (5), 972–90.

Kim, E.H., Morse, A., Zingales, L. (2009) Are elite universities losing their competitive edge. *Journal of Financial Economics*, 93, 353–381.

Kornhauser, W. (1962) *Scientists in industry: Conflict and accommodation*. Berkeley: University of California Press.

Krohn, R.C. (1961) The institutional location of the scientist and his scientific values. *I.R.E. Transactions on Engineering Management*, 8, 133-38.

Levin, S.G. and Stephan, P.E. (1991) Research productivity over the life cycle: Evidence for academic scientists. *American Economic Review*, 81, 114–132.

Long, J.S. and McGinnis, R. (1981) Organizational context and scientific productivity. *American Sociological Review*, 46, 422-442.

Marcson, S. (1960) *The scientist in American industry*. Princenton, Princenton University Press.

Merton, R.K. (1968) The Matthew effect in science. *Science*, 159, 56-63.

Meyer, J.B. (2001) Network approaches versus brain drain lessons from the diaspora. *International Migration*, 39 (5) Special Issue 1, 99-110.

Møen, J. (2005) Is mobility of technical personnel a source of R&D Spillovers? *Journal of Labor Economics*, 23, 81-114.

Mortensen D. (1986) Job search and labor market analysis. In O. Ashenfelter and R. Layard (eds) Handbook of Labour Economics, Volume 2, Amsterdam: North Holland.

Murray, F. (2011) The Oncomouse that roared: Hybrid exchange strategies as a source of productive tension at the boundary of overlapping institutions. *American Journal of Sociology*, forthcoming.

Oyer, P. (2007) Is there an insider advantage in getting tenure?. *The American Economic Review*, 97 (2) 501-505.

Oyer, P. (2008) Ability and employer learning : Evidence from the economist labor market. *Journal of Japanese and International Economies*, 22, 268-289

Pakes, A. and Nitzan, S. (1983) Optimum contracts for research personnel, research employment, and the establishment of 'rival' enterprises. *Journal of Labor Economics*, 1, 345-365.

Sauermann, H. and Roach, M. (2011) The price of silence: Scientists' trade-offs between pay and the ability to publish, paper presented to the BRICK workshop The Organization, Economics and Policy of Scientific Research, Univeristy of Turin, Turin (I).

Shaw, K. (1987) Occupational change, employer change, and the transferability of skills'. *Southern Economic Journal*, 53 (3), 702-718.

Stern, S. (2004) Do scientists pay to be scientists? *Management Science*, 50 (6), 835-853.

UNESCO (2005) Tertiary students abroad. Learning without borders. Montral, Canada: UIS.

van Heeringen, A. and Dijkwel, P.A. (1987) Effect of mobility on productivity. *Scientometrics*, 11, 267-280.

Waldinger, F. (2010) Peer effects in science - Evidence from the dismissal of scientists in Nazi Germany. *Review of Economic Studies*, forthcoming.

Weinberg, B.A. (2007) Geography and innovation: Evidence from Nobel physicists, Ohio State University

Ziman, J. (1991) Public understanding of science. *Sci Technol Human Values*, 16 (1), 99–105

Zubieta, A.F. (2009) Recognition and weak ties: Is there a positive effect of postdoctoral position on academic performance and career development? *Research Evaluation*, 18, 105-115.

Zucker, L.G., Darby, M.R. and Marilynn, B. (1998) Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review*, 88, 290-306.

Zucker, L.G., Darby, M.R. and Torero, M. (2002) Labor mobility from academe to commerce. *Journal of Labor Economics*, 20, 629-660.

Zuckerman, H. and Merton, R.K. (1973) Age, aging and age structure in science. In R.K. Merton, (ed.) *The sociology of science*. Chicago: Chicago University Press. 493–560.

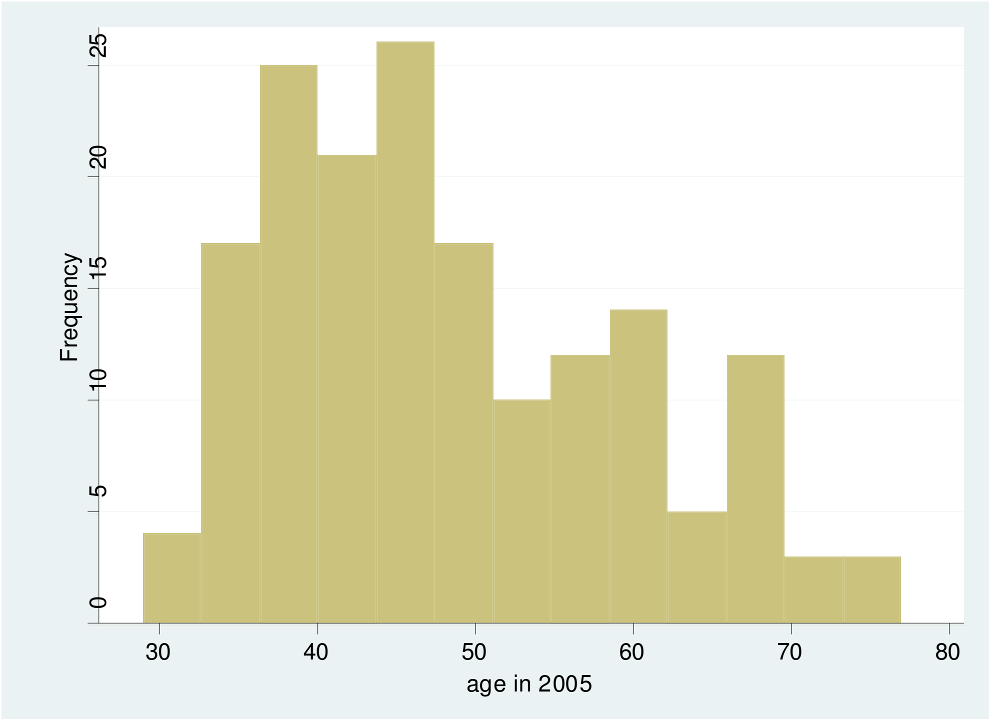

Figure 1

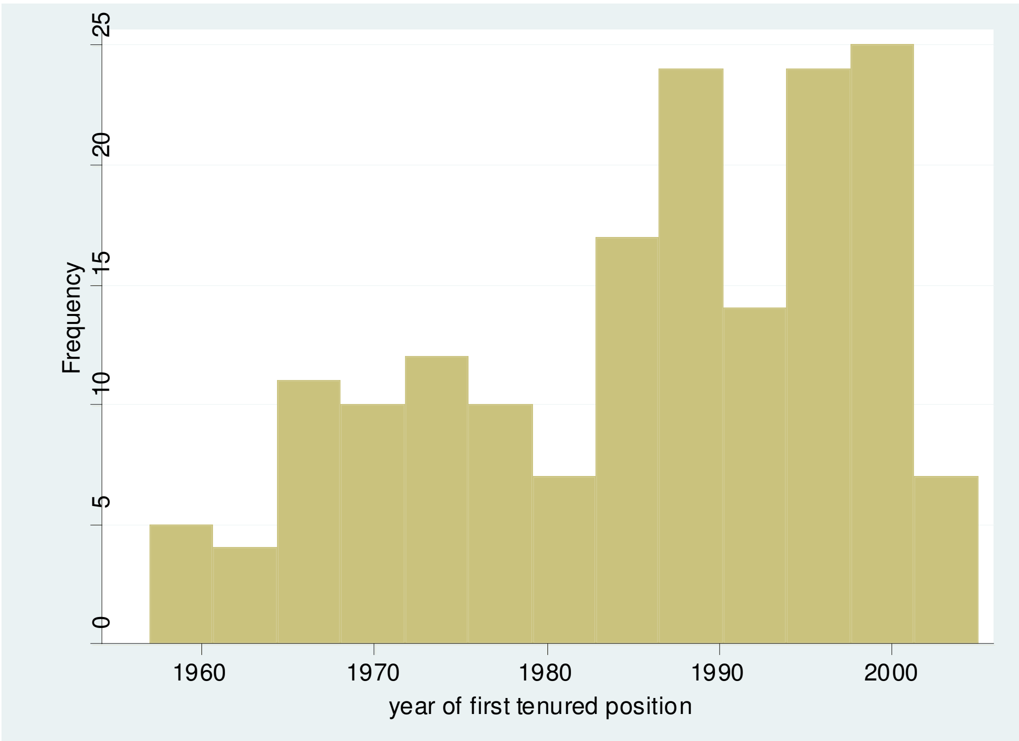

Figure 2

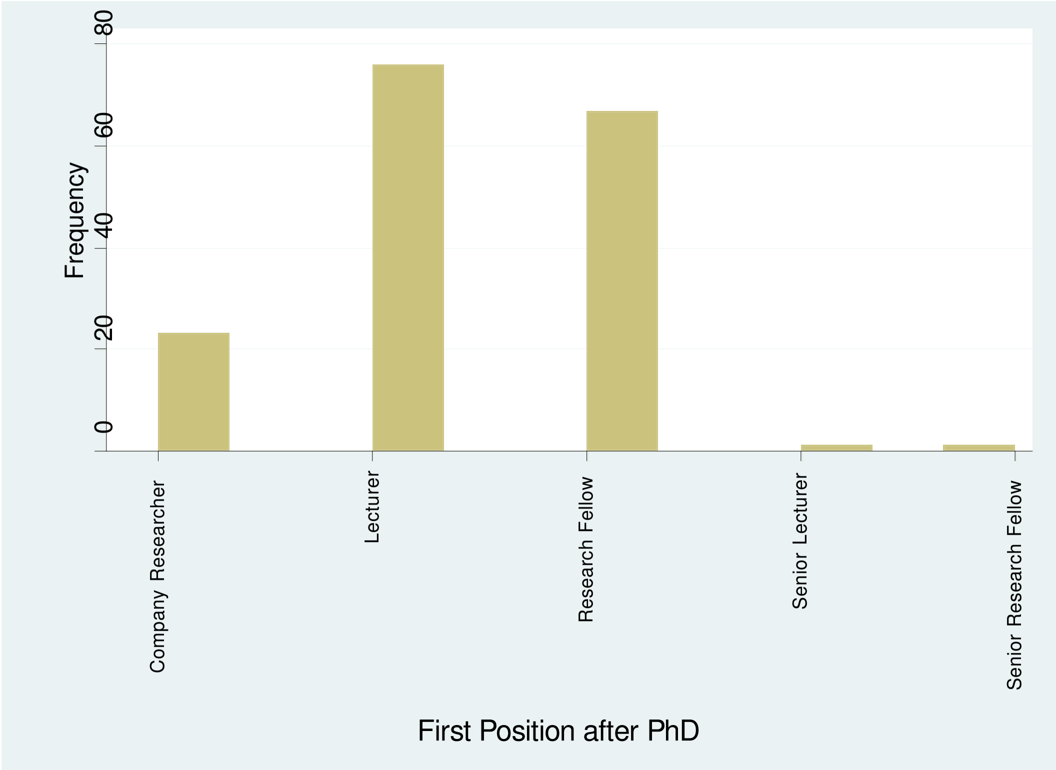

Figure 3

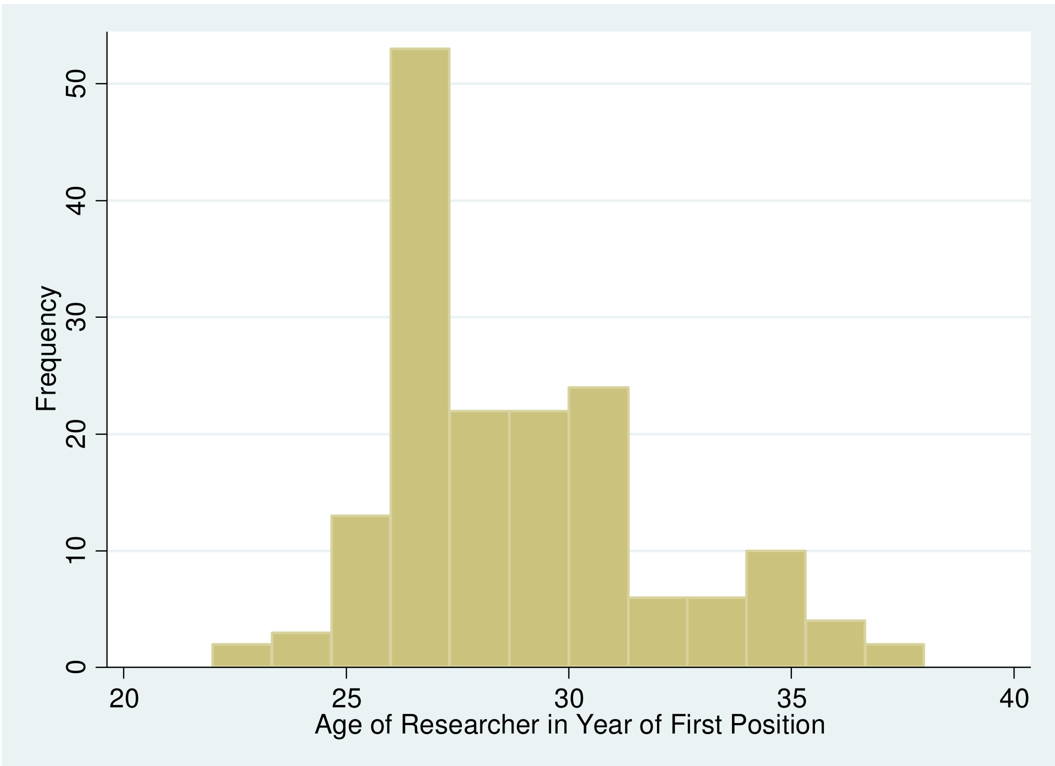

Figure 4

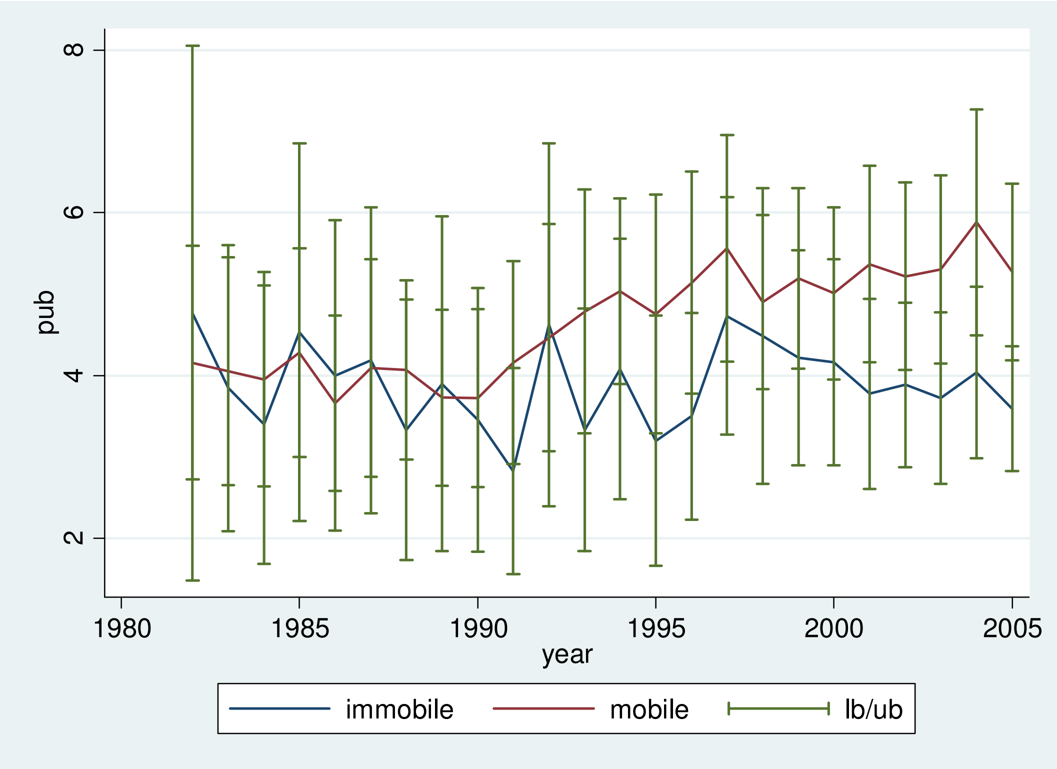

Figure 5: Average publication numbers for mobile and immobile academics

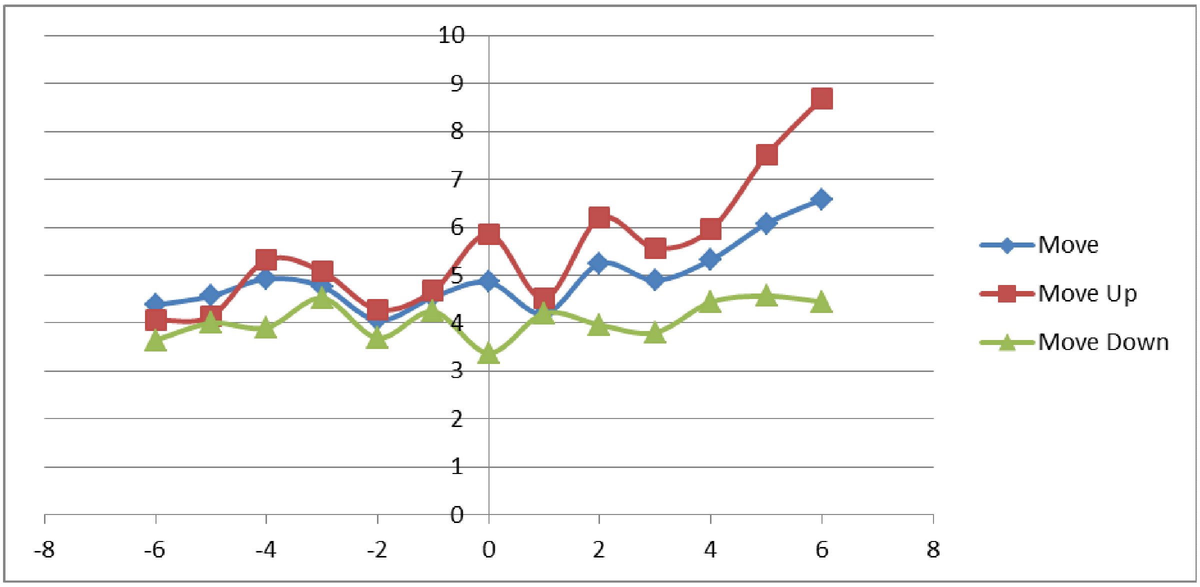

Figure 6: Years since Move

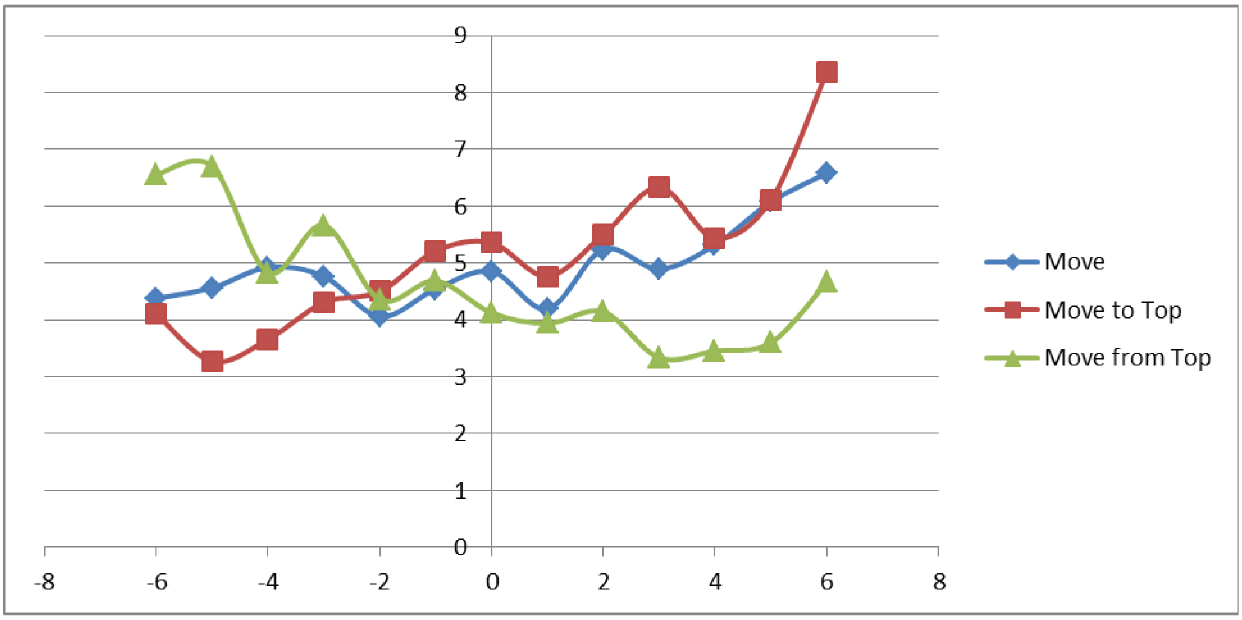

Figure 7: Mobility to and from the top 10-percentile departments

Table 1: Definition and Summary Statistics 1980-2005

VARIABLES		Mean	SD	Min	Max
PUB_{it}	Number of publications in *t*	4.53	5.07	0	54
MOB_{it}	Dummy = 1 if Job transition in *t*	.044	.205		
$UNIMOB_{it}$	Dummy = 1 if Job transition Between UK universities	.023	.152		
$MOVEUP_{it}$	Dummy = 1 if Job transition to a higher ranked department	.009	.095		
$MOVEDOWN_{it}$	Dummy = 1 if Job transition to a lower ranked department	.011	.103		
$INDMOVE_{it}$	Dummy = 1 if Job transition from industry to academia	.010	.099		
PROMOTION	Dummy = 1 if job transition accompanied by promotion	.017	.013		
AGE_{it}	Age in *t*	42.64	10.28	25	77
$MALE_i$	Dummy = 1 if male	.887	.315		
$RANK1_{it-1}$	Dummy = 1 if Lecturer in *t*	.276	.447		
$RANK2_{it-1}$	Dummy = 1 if Senior position in *t*	.326	.468		
$RANK3_{it-1}$	Dummy = 1 if Professor in *t*	.306	.461		
$FIRM_{it-1}$	Dummy = 1 if working in Industry in *t*	.090	.286		
$INDEXP_{it}$	Dummy=1 if experience in Industry in *t*	.128	.335		
POSTDOC $SHORT_i$	Dummy = 1 if postdoc of 1-3 Years	.325	.468		
POSTDOC $LONG_i$	Dummy = 1 if postdoc of 4 years or more	.113	.317		
$CHEMISTRY_i$	Dummy = 1 if working in Chemistry	.392	.488		
$PHYSICS_i$	Dummy = 1 if working in Physics	.339	.473		
$COMPUTER_i$	Dummy = 1 if working in Computer Science	.131	.337		
$MECHANICAL_i$	Dummy = 1 if working in Mechanical Engineering	.137	.344		

Table 2: Negative Binomial Regression of mobility on publication numbers

	(1)	(2)	(3)	(4)	(5)	(6)
		MOB			UNIMOB	
VARIABLES			Dependent Variable: PUB			
Fixed Effect$_i$	0.0576***	0.0619***	0.0619***	0.0522***	0.0569***	0.0568***
	(0.0184)	(0.0179)	(0.0179)	(0.0196)	(0.0188)	(0.0188)
MOB/UNIMOB$_{it-1}$	-0.132	-0.0680	-0.0706	-0.159	-0.139	-0.156
	(0.0950)	(0.110)	(0.107)	(0.114)	(0.147)	(0.141)
MOB/UNIMOB$_{it-2}$	0.0218	0.0702	0.0645	0.0773	0.0979	0.0812
	(0.0895)	(0.105)	(0.0970)	(0.108)	(0.132)	(0.121)
MOB/UNIMOB$_{it-3}$	0.0209	0.0261	0.0219	-0.0595	-0.100	-0.104
	(0.0869)	(0.107)	(0.0974)	(0.122)	(0.157)	(0.141)
MOB/UNIMOB$_{it-4}$		-0.0525			-0.0337	
		(0.0938)			(0.130)	
MOB/UNIMOB$_{it-5}$		0.0977			0.104	
		(0.0821)			(0.131)	
MOB/UNIMOB$_{it-6}$		0.0736			0.269**	
		(0.0861)			(0.131)	
INDEXP$_{it-1}$	-0.146	-0.132	-0.127			
	(0.147)	(0.147)	(0.147)			
FIRM $_{it-1}$	-0.399*	-0.324	-0.327			
	(0.205)	(0.223)	(0.222)			
AGE$_{it}$	0.0589	0.0461	0.0462	0.0473	0.0303	0.0289
	(0.0429)	(0.0472)	(0.0470)	(0.0521)	(0.0583)	(0.0582)
AGE$^2_{it}$	-0.000592	-0.000464	-0.000467	-0.000586	-0.000419	-0.000412
	(0.000462)	(0.000497)	(0.000497)	(0.000582)	(0.000633)	(0.000634)
RANK1$_{it-1}$			omitted category			
RANK2$_{it-1}$	0.241**	0.319**	0.320**	0.306***	0.352**	0.362**
	(0.106)	(0.130)	(0.130)	(0.116)	(0.143)	(0.145)
RANK3$_{it-1}$	0.266*	0.336**	0.336**	0.537***	0.585***	0.589***
	(0.142)	(0.145)	(0.145)	(0.164)	(0.171)	(0.172)
MALE$_i$	-0.0583	-0.0458	-0.0479	-0.276	-0.257	-0.268
	(0.198)	(0.172)	(0.175)	(0.250)	(0.226)	(0.237)
POSTDOC SHORT$_i$	-0.168	-0.194	-0.192	-0.254*	-0.270*	-0.267*
	(0.119)	(0.120)	(0.120)	(0.150)	(0.155)	(0.155)
POSTDOC LONG$_i$	-0.336*	-0.320*	-0.321*	-0.323	-0.278	-0.283
	(0.184)	(0.190)	(0.189)	(0.216)	(0.221)	(0.220)
CHEMISTRY$_i$			omitted category			
PHYSICS$_i$	-0.210*	-0.219*	-0.219*	-0.274*	-0.313**	-0.315**
	(0.127)	(0.128)	(0.128)	(0.141)	(0.143)	(0.143)
COMPUTER$_i$	-1.390***	-1.388***	-1.387***	-1.481***	-1.366***	-1.381***
	(0.177)	(0.181)	(0.181)	(0.239)	(0.279)	(0.279)
MECHANICAL$_i$	-0.771***	-0.722***	-0.719***	-0.918***	-0.842***	-0.831***
	(0.192)	(0.191)	(0.191)	(0.263)	(0.259)	(0.261)
Constant	0.296	0.508	0.529	0.921	1.238	1.337
	(0.948)	(1.089)	(1.078)	(1.124)	(1.301)	(1.300)
lnalpha	-0.835***	-0.910***	-0.907***	-0.894***	-0.974***	-0.968***
log-likelihood	-5457	-4750	-4752	-3716	-3184	-3186
Observations	2,222	1,901	1,901	1,432	1,201	1,201

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3: Negative Binomial Regression of up- and downward mobility on publication numbers

	(1)	(2)	(3)	(4)	(5)	(6)
		MOVEUP			MOVEDOWN	
VARIABLES			Dependent Variable: PUB			
Fixed Effect$_i$	0.0443**	0.0444**	0.0430**	0.0449**	0.0451***	0.0437**
	(0.0196)	(0.0178)	(0.0179)	(0.0194)	(0.0172)	(0.0176)
MOVEUP/MOVEDOWN$_{it-1}$	-0.0959	0.000405	-0.0338	-0.0735	-0.124	-0.101
	(0.143)	(0.167)	(0.150)	(0.201)	(0.250)	(0.245)
MOVEUP/MOVEDOWN$_{it-2}$	0.231	0.259	0.233	-0.103	-0.195	-0.166
	(0.173)	(0.207)	(0.187)	(0.170)	(0.217)	(0.208)
MOVEUP/MOVEDOWN$_{it-3}$	-0.00348	-0.0117	-0.0145	-0.310*	-0.539***	-0.503***
	(0.154)	(0.209)	(0.182)	(0.164)	(0.197)	(0.189)
MOVEUP/MOVEDOWN$_{it-4}$		0.143			-0.491**	
		(0.174)			(0.208)	
MOVEUP/MOVEDOWN$_{it-5}$		0.320			-0.321	
		(0.223)			(0.197)	
MOVEUP/MOVEDOWN$_{it-6}$		0.565***			-0.215	
		(0.166)			(0.212)	
AGE$_{it}$	0.0472	0.0191	0.0201	0.0439	0.00524	0.0131
	(0.0566)	(0.0685)	(0.0682)	(0.0566)	(0.0683)	(0.0681)
AGE$^2_{it}$	-0.000575	-0.000304	-0.000323	-0.000550	-0.000203	-0.000266
	(0.000623)	(0.000726)	(0.000724)	(0.000623)	(0.000724)	(0.000723)
RANK1$_{it-1}$			omitted category			
RANK2$_{it-1}$	0.310**	0.367**	0.381**	0.317***	0.396**	0.386**
	(0.121)	(0.152)	(0.157)	(0.122)	(0.156)	(0.156)
RANK3$_{it-1}$	0.548***	0.659***	0.647***	0.561***	0.694***	0.670***
	(0.166)	(0.183)	(0.187)	(0.170)	(0.189)	(0.190)
MALE$_i$	-0.262	-0.245	-0.264	-0.267	-0.292	-0.282
	(0.259)	(0.233)	(0.258)	(0.262)	(0.264)	(0.267)
POSTDOC SHORT$_i$	-0.264*	-0.311**	-0.314*	-0.266*	-0.318**	-0.319*
	(0.157)	(0.158)	(0.162)	(0.157)	(0.161)	(0.163)
POSTDOC LONG$_i$	-0.318	-0.284	-0.287	-0.317	-0.282	-0.284
	(0.230)	(0.234)	(0.237)	(0.230)	(0.231)	(0.236)
CHEMISTRY$_i$			omitted category			
PHYSICS$_i$	-0.254*	-0.256*	-0.279*	-0.257*	-0.285**	-0.282*
	(0.144)	(0.143)	(0.146)	(0.144)	(0.144)	(0.146)
COMPUTER$_i$	-1.503***	-1.375***	-1.425***	-1.500***	-1.428***	-1.432***
	(0.240)	(0.272)	(0.278)	(0.239)	(0.266)	(0.275)
MECHANICAL$_i$	-0.926***	-0.868***	-0.874***	-0.915***	-0.818***	-0.853***
	(0.275)	(0.276)	(0.285)	(0.278)	(0.296)	(0.290)

Constant	0.904	1.479	1.551	1.000	1.999	1.758
	(1.220)	(1.540)	(1.529)	(1.230)	(1.547)	(1.534)
lnalpha	-0.841***	-0.912***	-0.892***	-0.843***	-0.911***	-0.897***
Log-Likelihood	-3375	-2656	-2662	-3374	-2655	-2660
Observations	1,292	992	992	1,292	992	992

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4: Negative Binomial Regression of up- and downward mobility with career progression on publication numbers

	(1)	(2)	(3)	(4)	(5)	(6)
		MOVEUP			MOVEDOWN	
VARIABLES			Dependent Variable: PUB			
Fixed Effect$_{i}$	0.0252	0.0304**	0.0267*	0.0235	0.0255	0.0242
	(0.0182)	(0.0148)	(0.0161)	(0.0194)	(0.0173)	(0.0171)
MOVEUP/MOVEDOWN$_{it-1}$	-0.402**	-0.359*	-0.362*	-0.158	0.000441	-0.00606
	(0.197)	(0.195)	(0.197)	(0.216)	(0.268)	(0.261)
MOVEUP/MOVEDOWN$_{it-2}$	0.133	0.0181	0.0175	0.0428	0.437	0.411
	(0.218)	(0.212)	(0.215)	(0.266)	(0.380)	(0.366)
MOVEUP/MOVEDOWN$_{it-3}$	-0.289	-0.378	-0.387	0.176	0.0383	0.0378
	(0.238)	(0.278)	(0.273)	(0.235)	(0.238)	(0.218)
MOVEUP/MOVEDOWN$_{it-4}$		-0.183			-0.337	
		(0.172)			(0.239)	
MOVEUP/MOVEDOWN$_{it-5}$		-0.0959			-0.276	
		(0.172)			(0.225)	
MOVEUP/MOVEDOWN$_{it-6}$		0.278*			0.409	
		(0.156)			(0.404)	
Promotion$_{it-1}$	-0.0615	-0.0870	-0.103	-0.0466	-0.101	-0.0808
	(0.114)	(0.150)	(0.127)	(0.110)	(0.144)	(0.123)
Promotion$_{it-2}$	-0.0402	-0.0704	-0.0890	0.00682	-0.0164	-0.00425
	(0.0877)	(0.115)	(0.0948)	(0.0821)	(0.110)	(0.0866)
Promotion$_{it-3}$	-0.0655	-0.0682	-0.0959	0.0269	-0.0167	-0.00114
	(0.101)	(0.132)	(0.108)	(0.0980)	(0.124)	(0.0978)
Promotion$_{it-4}$		-0.0748			-0.0133	
		(0.111)			(0.110)	
Promotion$_{it-5}$		-0.0149			0.0614	
		(0.106)			(0.115)	
Promotion$_{it-6}$		0.0345			0.166*	
		(0.0923)			(0.0984)	
Promotion*MOVEUP/MOVEDOWN$_{it-1}$	0.711**	0.821**	0.713**	0.157	-0.0887	-0.0949
	(0.286)	(0.364)	(0.319)	(0.345)	(0.443)	(0.442)
Promotion*MOVEUP/MOVEDOWN$_{it-2}$	0.189	0.577	0.501	-0.232	-0.883*	-0.850*
	(0.399)	(0.482)	(0.434)	(0.337)	(0.458)	(0.450)
Promotion*MOVEUP/MOVEDOWN$_{it-3}$	0.684**	0.821**	0.816**	-0.744**	-0.779**	-0.765**
	(0.329)	(0.410)	(0.360)	(0.312)	(0.327)	(0.315)
Promotion*MOVEUP/MOVEDOWN$_{it-4}$		0.734*			-0.178	
		(0.397)			(0.352)	
Promotion*MOVEUP/MOVEDOWN$_{it-5}$		0.874*			-0.0902	
		(0.474)			(0.351)	
Promotion*MOVEUP/MOVEDOWN$_{it-6}$		0.575			-1.003**	
		(0.362)			(0.440)	
AGE$_{it}$	0.0505	0.0139	0.0180	0.0509	0.00561	0.0142
	(0.0597)	(0.0741)	(0.0723)	(0.0598)	(0.0738)	(0.0723)
AGE$^{2}_{it}$	-0.000571	-0.000212	-0.000272	-0.000583	-0.000176	-0.000250
	(0.000646)	(0.000766)	(0.000756)	(0.000646)	(0.000764)	(0.000755)
RANK1$_{it-1}$			omitted category			
RANK2$_{it-1}$	0.305**	0.335*	0.382**	0.324**	0.429**	0.416**
	(0.151)	(0.187)	(0.174)	(0.149)	(0.183)	(0.171)
RANK3$_{it-1}$	0.594***	0.675**	0.713***	0.617***	0.776***	0.759***
	(0.214)	(0.267)	(0.233)	(0.213)	(0.262)	(0.231)

MALE$_i$	-0.224	-0.154	-0.232	-0.242	-0.269	-0.270
	(0.229)	(0.183)	(0.226)	(0.244)	(0.247)	(0.250)
POSTDOC SHORT$_i$	-0.269*	-0.314*	-0.327*	-0.272*	-0.339**	-0.338*
	(0.163)	(0.166)	(0.171)	(0.164)	(0.171)	(0.173)
POSTDOC LONG$_i$	-0.365	-0.293	-0.318	-0.376	-0.339	-0.341
	(0.237)	(0.244)	(0.245)	(0.235)	(0.234)	(0.240)
CHEMISTRY$_i$	omitted category					
PHYSICS$_i$	-0.321**	-0.338**	-0.353**	-0.321**	-0.360**	-0.353**
	(0.153)	(0.157)	(0.157)	(0.153)	(0.155)	(0.157)
COMPUTER$_i$	-1.606***	-1.471***	-1.522***	-1.617***	-1.550***	-1.552***
	(0.246)	(0.286)	(0.288)	(0.247)	(0.275)	(0.284)
MECHANICAL$_i$	-1.075***	-1.049***	-1.018***	-1.070***	-1.041***	-1.034***
	(0.266)	(0.274)	(0.282)	(0.273)	(0.299)	(0.290)
Constant	0.830	1.571	1.610	0.841	1.953	1.739
	(1.303)	(1.693)	(1.635)	(1.309)	(1.706)	(1.640)
lnalpha	-0.802***	-0.892***	-0.856***	-0.797***	-0.872***	-0.853***
Log-Likelihood	-3390	-2663	-2673	-3391	-2665	-2672
Observations	1,292	992	992	1,292	992	992

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5: Negative Binomial Regression of mobility to or out of the top 10 percentile on publication numbers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Move to top			Move in top			Move from top
VARIABLES					Dependent variable: PUB			
Fixed Effect$_i$	0.0243	0.0249	0.0250	0.0239	0.0240	0.0241	0.0244	0.0260
	(0.0188)	(0.0170)	(0.0169)	(0.0190)	(0.0168)	(0.0169)	(0.0191)	(0.0170)
MOB$_{it-1}$	-0.162	-0.253*	-0.262*	-0.0972	-0.190	-0.179	-0.313	-0.445
	(0.169)	(0.145)	(0.139)	(0.242)	(0.295)	(0.295)	(0.316)	(0.448)
MOB$_{it-2}$	-0.211	-0.144	-0.158	-0.256	-0.432	-0.418	-0.0930	-0.133
	(0.169)	(0.180)	(0.175)	(0.322)	(0.370)	(0.367)	(0.172)	(0.239)
MOB$_{it-3}$	-0.148	-0.190	-0.208	-0.330	-0.255	-0.242	0.0479	-0.150
	(0.234)	(0.262)	(0.247)	(0.328)	(0.357)	(0.354)	(0.195)	(0.269)
MOB$_{it-4}$		-0.120			-0.487*			-0.133
		(0.187)			(0.249)			(0.309)
MOB$_{it-5}$		0.0225			-0.152			-0.200
		(0.198)			(0.227)			(0.240)
MOB$_{it-6}$		0.545**			-0.222			-0.164
		(0.224)			(0.337)			(0.164)
AGE$_{it}$	0.0535	0.0263	0.0251	0.0537	0.0226	0.0264	0.0529	0.0212
	(0.0585)	(0.0703)	(0.0703)	(0.0583)	(0.0701)	(0.0701)	(0.0587)	(0.0709)
AGE$^2_{it}$	-0.000600	-0.000348	-0.000337	-0.000606	-0.000323	-0.000354	-0.000597	-0.000309
	(0.000639)	(0.000741)	(0.000742)	(0.000639)	(0.000742)	(0.000743)	(0.000640)	(0.000746)
RANK1$_{it-1}$					omitted category			
RANK2$_{it-1}$	0.301**	0.372**	0.375**	0.305**	0.385**	0.377**	0.307**	0.390**
	(0.132)	(0.165)	(0.165)	(0.130)	(0.163)	(0.163)	(0.132)	(0.164)
RANK3$_{it-1}$	0.584***	0.693***	0.688***	0.599***	0.725***	0.706***	0.596***	0.715***
	(0.178)	(0.199)	(0.200)	(0.179)	(0.201)	(0.199)	(0.180)	(0.204)
MALE$_i$	-0.239	-0.261	-0.255	-0.241	-0.257	-0.258	-0.245	-0.265
	(0.243)	(0.250)	(0.250)	(0.243)	(0.250)	(0.249)	(0.243)	(0.247)
POSTDOC SHORT$_i$	-0.269	-0.331*	-0.326*	-0.266	-0.322*	-0.325*	-0.271	-0.333*
	(0.164)	(0.173)	(0.173)	(0.164)	(0.172)	(0.173)	(0.165)	(0.174)
POSTDOC LONG$_i$	-0.379	-0.348	-0.350	-0.375	-0.342	-0.346	-0.375	-0.344
	(0.238)	(0.246)	(0.246)	(0.237)	(0.241)	(0.244)	(0.238)	(0.246)
CHEMISTRY$_i$					omitted category			
PHYSICS$_i$	-0.325**	-0.352**	-0.356**	-0.322**	-0.349**	-0.349**	-0.321**	-0.351**
	(0.154)	(0.159)	(0.159)	(0.153)	(0.157)	(0.158)	(0.153)	(0.158)
COMPUTER$_i$	-1.622***	-1.548***	-1.558***	-1.625***	-1.562***	-1.556***	-1.615***	-1.563***
	(0.248)	(0.294)	(0.294)	(0.249)	(0.293)	(0.293)	(0.249)	(0.293)
MECHANICAL$_i$	-1.063***	-1.024***	-1.015***	-1.060***	-1.001***	-1.004***	-1.064***	-1.014***
	(0.267)	(0.274)	(0.279)	(0.265)	(0.276)	(0.278)	(0.265)	(0.279)
Constant	0.780	1.434	1.469	0.774	1.541	1.442	0.789	1.587
	(1.265)	(1.582)	(1.575)	(1.256)	(1.562)	(1.561)	(1.273)	(1.600)
lnalpha	-0.792***	-0.849***	-0.842***	-0.791***	-0.846***	-0.842***	-0.792***	-0.843***
Log-Likelihood	-3394	-2674	-2676	-3393	-2675	-2676	-3394	-2675
Observations	1,292	992	992	1,292	992	992	1,292	992

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Negative Binomial Regression of industry mobility on publication numbers

	(1)	(2)	(3)
		INDMOVE	
VARIABLES		Dependent Variable: PUB	
Fixed Effect$_i$	0.0582***	0.0626***	0.0623***
	(0.0187)	(0.0182)	(0.0181)
INDMOVEit-1	-0.586**	-0.585**	-0.587**
	(0.228)	(0.278)	(0.275)
INDMOVEit-2	-0.469**	-0.415*	-0.421**
	(0.207)	(0.219)	(0.212)
NDMOVEit-3	0.118	0.167	0.159
	(0.171)	(0.168)	(0.163)
INDMOVEit-4		0.0164	
		(0.215)	
INDMOVEit-5		0.233	
		(0.178)	
INDMOVEit-6		0.0779	
		(0.165)	
AGE_{it}	0.0543	0.0389	0.0391
	(0.0433)	(0.0475)	(0.0476)
AGE^2_{it}	-0.000560	-0.000412	-0.000413
	(0.000472)	(0.000507)	(0.000507)
$RANK1_{it-1}$		omitted category	
$RANK2_{it-1}$	0.237**	0.316**	0.319**
	(0.103)	(0.127)	(0.128)
$RANK3_{it-1}$	0.299**	0.377***	0.374***
	(0.138)	(0.141)	(0.143)
$MALE_i$	-0.137	-0.129	-0.126
	(0.205)	(0.184)	(0.184)
POSTDOC SHORT$_i$	-0.175	-0.194	-0.195
	(0.120)	(0.122)	(0.122)
POSTDOC LONG$_i$	-0.313*	-0.305	-0.307
	(0.187)	(0.192)	(0.192)
$CHEMISTRY_i$		omitted category	
$PHYSICS_i$	-0.226*	-0.243*	-0.238*
	(0.131)	(0.131)	(0.132)
$COMPUTER_i$	-1.342***	-1.348***	-1.344***
	(0.184)	(0.194)	(0.194)
$MECHANICAL_i$	-0.790***	-0.730***	-0.725***
	(0.183)	(0.184)	(0.185)
Constant	0.450	0.762	0.755
	(0.960)	(1.091)	(1.093)
lnalpha	-0.870***	-0.940***	-0.938***
Log-Likelihood	-5098	-4458	-4459
Observations	2,030	1,750	1,750

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1