Mobility and Productivity of Research Scientists

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[1] Some of the material presented in this chapter is also discussed in Fernández-Zubieta et al. (2015).

Abstract

This chapter presents a framework to analyze the effects of mobility on academic performance. In a research system characterized by its internationalization, increasing inter-sector collaboration, and diversification of work roles and careers, we maintain that in order to properly analyze the effects of mobility on academic performance it is necessary to take account of different types of mobility events and short and long-term return opportunities. We apply our framework to a sample of 171 UK academic researchers and find no evidence that mobility per se increases academic performance, but that mobility to a higher ranked department has a positive weakly significant impact, while downward mobility reduces researchers' productivity (in terms of quantity and quality). Job mobility is always associated with a short-term decrease in performance, arguably due to adjustment costs. Inter-sector mobility is also associated with an initial short-term publication disadvantage which appears to vanish soon after joining academia, making the overall performance of researchers that move to academia from industry not significantly different from that of pure academics.

Keywords: Academic labor market, Research performance, Researcher mobility

JEL codes: O31, I23, J24

1. Introduction

Researcher mobility between institutions, disciplines, sectors, and countries is increasingly being encouraged at policy level (OECD 2000; EC 2001; EC 2006; EC 2012) as an instrument to improve the performance of the research system by facilitating knowledge and technology transfer, and to increase productivity. The assumed positive effects of researcher mobility are related to the embedded nature of knowledge (Griliches 1973; Granovetter 1985). Mobility allows researchers to spread and increase their human (Schultz 1961, 1990; Becker 1962, 1964; Nelson and Phelps 1966) and social capital (Bourdieu 1986; Coleman 1988; Burt 1997). This transfer and augmentation of human and social capital can have positive effects on researchers' performance, patterns of collaboration, and career development. This perspective, thus assumes that both the research system and the individual researcher benefit from mobility. However, to date there is scant evidence on researcher mobility and its consequences (Teichler 1996; Musselin 2004; Franzoni et al. 2012).

Changes to the research system require researchers to be able to adapt to new institutions, sectors and work roles. They also require institutions to properly manage mobile researchers and their careers. Researchers moving across sectors, or moving as a result of career advancement, can facilitate the knowledge and technology transfer process and gain access to knowledge, equipment, and networks that could improve their performance. We propose a framework to analyze the individual effects of researcher mobility on research performance, based on a job-matching approach (Jovanovic 1979; Mortensen 1986) adapted for academics that emphasizes research and reputation factors. Drawing on the idea that academic performance is driven by the availability of capital— both human and social— and peer effects (Weinberg 2007; Azoulay et al. 2010; Waldinger 2012), we hypothesize different short and medium-term effects of mobility on research performance. We test our predictions with a sample of 171 mobile and non-mobile UK academic researchers in science and engineering for which we collected information on employment patterns and publishing activities over their entire career up to 2005, covering a period from 1957 to 2005. We find no evidence that mobility per se boosts the scientific productivity of researchers; what matters is the destination. Mobility to a lower ranked university is accompanied by a decrease in the number of publications, while mobility to a higher ranked university is associated with a positive increase in productivity, but no quality effect. In both cases we find strong evidence of short-term negative effects. Inter-sector mobility, i.e. mobility from industry to academia, does not affect publication rates, making researchers with a background in industry as productive as their purely academic peers.

2. The effect of researcher mobility on researcher productivity

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

The impact of a job change (*M)* on scientific productivity (*sp*) is affected by the researcher's reasons for the move. For example, job mobility may have a positive impact on research productivity only if the researcher finds better conditions for pursuing her research endeavor in the new job location - in other words, if she moves to a new job in order to increase her research performance. Thus, a researcher moves to a new job if the value V_{t+1} of her utility function is higher than the value V_t before the move at time t. This may be due to traditional job search related factors (e.g. wages, search efforts, mobility cost), 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 *(r)* can we expect a positive impact on performance.

Hence, we do not expect all types of job mobility to be associated with increased research productivity.

Following from the above we consider the following function for scientific productivity:

$$sp = f(M(r), pt, pf, h) \qquad (1)$$

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

Although we expect mobility driven by research and reputational factors to result in better performance, there are accompanying mobility costs that negatively affect research productivity. The time needed to learn new tasks and administrative procedures in the new institution means that the mobile researcher will have less time to devote to research activities (Shaw 1987; Groysberg 2008). In addition, expected and real adjustments costs can differ which can have a negative impact on post-mobility productivity. Therefore, it is reasonable to expect a period of decreased productivity after the job change regardless of the reasons for the move. The length of the adjustment period and the intensity of the reduced productivity will depend on the specific adjustment costs.

To summarize, a job change will be associated with a positive effect on researchers' productivity only if it is motivated by research and reputational factors, and we should expect a decrease in productivity in the short term due to adjustment costs. Below we discuss how this plays out for two types of mobility observed in academia: social mobility and inter-sector mobility.[2]

Social mobility: a move to a higher ranked university

The search and match model predicts that researchers with high potential productivity will move from a lower quality department or university to a higher quality department or university (upward mobility), which provides a better research and reputation environment to realize their research potential.[3] A job move to a higher quality department provides access to better equipment (Martin-Rovet 2003), and a research group where the positive peer (Weinberg 2007)[4] and network effects are likely to increase the researcher's performance. In addition, mobile researchers can continue to benefit from their previous networks which are carried into the new environment (Azoulay et al. 2012; Waldinger 2012) creating extended networks, and possibilities for recombination, learning, collaboration, and productivity. Also, the Science and Technology (S&T) human capital theory (Bozeman and Rogers 2002) predicts that researchers acquire human and social capital through mobility, and supports the expected positive effect of mobility on productivity. Thus, job matching approach and human and social capital arguments can be combined to support the positive effects of upward job-mobility. A job move to a higher quality/reputation institution could lead to increased medium to long-term performance following an initial short period of decreased performance due to adjustments costs.

Inter-sector mobility: job move from industry to academia

Early analyses of inter-sector mobility (Marcson 1960; Krohn 1961; Kornhauser 1962;

[2] Ch. 1 of this book discusses various other possible mobility types.
[3] Oyer (2007) shows that highly productive researchers tend to be concentrated in highly ranked departments.
[4] However, Kim et al. (2009) find that peer-effects have decreased since 1990 (see also Ding et al. 2009).

Hagstrom 1965) show that differences in reward systems in different sectors can influence both the costs of job mobility and the mobile researcher's performance. The adaptation costs related to inter-sector job changes are expected to be higher than within sector mobility. Good matches for inter-sector job changes are also less likely since access to information about the new job is more difficult. Job mobility to a firm could direct the researcher's work to more applied matters, and discourage publications. Different priorities could negatively affect future scientific performance (Cotgrove and Box 1970) due to decreased accumulation of publishable knowledge. However, experience in industry could positively affect the performance of researchers returning to academia. Dietz and Bozeman (2005) analyze this side of the relationship and consider the productivity of researchers that have spent time in industry. They find a positive effect on patent productivity of years spent outside academia. Thus, while researchers involved in inter-sector job changes may suffer some adaptation costs, they may also benefit from presumed higher human capital acquired during their time in industry, and they may patent or publish more in the medium term.

Figure 1 summarizes the expected job mobility effects on academic performance across mobility types. In what follows we test these expectations empirically.

Figure 1. Job Mobility effects across mobility types

Job-mobility		***Social mobility*** *(*Upward mobility)	***Inter-sector mobility***
Short term	Medium term	Medium term	
(-)	(+) / (-)	(+)	(-) / (+)

3. Empirical analysis

3.1 Data

The empirical study is based on a sample of 171 research active academics working at 53 UK universities, in four scientific fields: chemistry, physics, computer science, and mechanical, aeronautical and manufacturing engineering in 2005.[5] We code career information taken from CVs in order to construct comprehensive profiles for the 171 researchers, spanning their careers from PhD award to 2005, resulting in a panel for the period 1957 to 2005. Researchers' CVs include unique information on career paths and the timing and nature of job transitions. This information was complemented with publication and citation data collected from the Web of Science (WoS).[6]

The three-step promotion system and race for positions in the most prestigious institutions (Hoare 1994) make the UK system more competitive than other academic systems in Europe. There is no obligation to move after PhD completion; however, mobility barriers are very low and mobility is usually rewarded, making the UK academic labor market very fluid. This makes the UK a suitable setting to test our approach. In the UK, the minimum tenure-track positions in academia are 'lecturer', followed by senior lecturer, reader, and professor. Since the early 1990s, in parallel with the traditional teaching and research academic career ladder a research only career[7] within the university system has developed, financed by soft money. Academics in the UK are usually hired on permanent contracts, which in the case of lecturer

[5] The sample is based on a 2004 survey of academic researchers awarded a grant from the Engineering and Physical Sciences Research Council (EPSRC) at least once between 1999 and 2003, who therefore can be considered research active. CVs were collected for a subsample of survey respondents. See Crespi et al. (2011) for a detailed description of the database.
[6] Using data collected from CVs combined with data from the ISI WoS improved the accuracy of our data since it avoids mismatches arising from common names, and changes in researchers' institutional affiliations.
[7] There are three type of research position: research fellow, senior research fellow and research professor. This career path has resulted in a greatly increased number of short-term contracts at research fellow level.

appointments or research fellowships,[8] are subject to a three-year probation period. Thus, job mobility in our sample is likely to be voluntary, i.e. based on researchers leaving a permanent position for reasons other than termination of contract.

Our sample consists of researchers aged 29 to 77 who were research active in 2005. The mean age of the sample is 49 in 2005. The first researcher joins our sample in 1957 and the last in 2003. Accordingly, the career years recorded in our sample range from 3 to 49, with an average observation period of 20 years. In our sample of 171 UK academics, 145 (85%) started out as lecturers or research fellows; 22 researchers (13%) took up a first position in industry, and 2 began their careers in senior academic positions. For another two researchers, first position was not evident from their CVs. The mean starting age is 28.6 with a minimum of 22 years and a maximum of 38 years.[9] The mean PhD age is slightly lower at 27.2 years. Among our researcher sample, 45.2% took up their first permanent position immediately after PhD award, while 48.8% embarked on a postdoc; 6% of the researchers in our sample started their work careers during or before studying for their PhD degree; 109 researchers (64%) changed jobs at least once during their career. In total, we have 159 job changes, with 31 academics changing positions twice during their career, 8 academics changing three times and 1 researcher moving four times. The mean number of years in one job is 10.

Although we consider only researchers that worked at UK universities in 2005, this includes researchers from outside the UK and researchers with an industry background. Along their careers, 28 researchers changed jobs between industry and academia, and 20 researchers moved internationally. Fifty researchers (29%) were born and raised outside the UK,

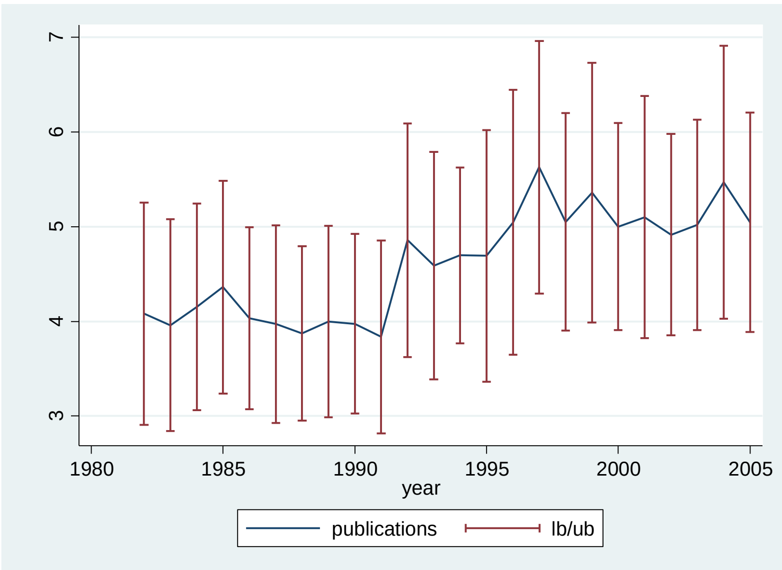
[8] We consider the position of research fellow as tenure-track equivalent to lecturer only if it persists for at least 5 years, indicating a long-term relationship with the university equivalent to a probation period

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

primarily in Europe (33 researchers). Researchers often move from their home country to take up a first permanent post: for 52 researchers the first permanent position is outside their country of birth which includes 11 UK-born researchers that took up a permanent position abroad. Nevertheless, the majority of researchers find a position in their country of birth (the median distance between first permanent job and place of birth is 176 miles).

Between 1982 and 2005, the academics in our sample produced an average of 4.45 publications per year. Eighty-eight researchers (59%) published their first article during their PhD study or postdoctoral period and before their first permanent position. The average number of publications per researcher per year increased from an average of 4.08 in 1982 to 5.05 in 2005 (Figure 2) with a similar increase in publication quality. Quality is measured as the number of WoS citations to a publication in the first five years after publication. Quality adjusted publication numbers increased from 46 in 1982, to 74 in 2005 which could be due to life-cycle, year, or mobility effects which this chapter attempts to measure.

Figure 2. Average publication numbers



3.2 Mobility and reputation: social mobility

In section 2 of this chapter, we stressed the importance of research and reputation factors for explaining the academic labor market. Access to resources and an improved research environment are incentives for mobility and are fundamental to an analysis of the impact of mobility on scientific productivity. In the period analyzed in this chapter, wages play a smaller role in the UK academic labor market, in particular because of the high level of standardization in UK academic salary scales.[10] Therefore, we assume that mobility is driven primarily by reputation factors, and classify job changes according to a move to a higher or a lower quality/reputation institution.

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

This measure of research reputation for a 23-year panel can be constructed only for UK universities. Thus, an econometric analysis making use of the ranking excludes mobility from

[10] Starting in 2004 (following the higher education pay framework) universities paid higher wages and offered higher incentive payments to higher reputation and more successful researchers.
[11] *Thomson Evidence* cleans UK address information found in WoS (taking account of university mergers) and completes missing records.
[12] See Fernández-Zubieta et al. (2013) for technical details on the ranking indicator.

companies (28 researchers), and those that are internationally mobile (8 researchers), leaving a sample of 108 researchers mobile within the UK.[13]

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

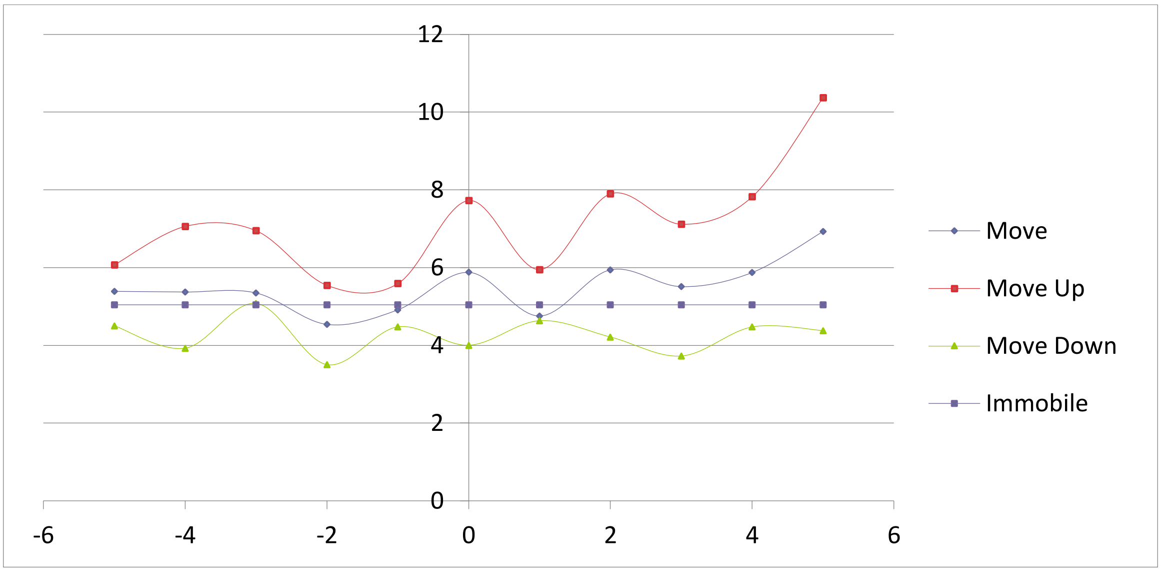
We define upward mobility as a move to a department ranked at least five percentile points higher than the previous department, in the year preceding the move (before the focal academic joined the new department), and downward mobility as a move to a department ranked at least five percentile points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

Figure 3 shows the mean number of publications for the five years prior to and following the move. We plot the graph for: the immobile sample, for all moves between UK universities, for upward mobility, and for downward mobility. We assume a one-year lag between the research and its publication. Thus, articles published in the year of the move (year zero) refer to research undertaken in the previous institutions. The disruption caused by the mobility event results in a decline in the publication pipeline, followed by decreased publication numbers in year 1 after the move. Figure 3 confirms the one-year lag between a move and publication. This may be a reflection of the mobility and adjustment costs which likely result in decreased research efficiency in year *t*. However, from year 2 onwards the number of

[13] We had to exclude a further 19 researchers due to incomplete information on year of promotion.
[14] We observed 15 lateral moves, i.e. moves between universities of equal or similar ranking. These are not analyzed separately here.

publications increases. In the case of downward mobility, publication rates do not improve. On average, a mobile researcher making a downward move performs worse than a non-mobile researcher. An upward mobile researcher even in the years prior to the move produces a higher number of publications than a downward mobile or non-mobile researcher. Hence, academics moving to higher quality institutions are already performing above the average before the move, while academics moving to less prestigious universities are showing below average performance. The difference between the two groups increases further in the years following the move. The graph in Figure 3 is consistent with the results in Allison and Long (1990) regarding the positive effects of department quality on productivity but in contrast to their results, our results shows that the upward mobile group starts out with higher productivity than the downward mobile group which supports our job-match hypothesis.

Figure 3. Publication numbers in years since move for academics working at UK universities



3.3 Econometric specification

We use count data models to estimate the effect of mobility on publications, since numbers of publications and citations are positive count values. The data are characterized by overdispersion which we account for by using pooled negative binomial models that take the form:

$$E(sp'_{it}\,|M_{it}, X_{it}, c_i) = \exp\{\beta_1 M_{it} + \beta_2 X_{it} + c_i + \tau_t + \upsilon_{it}\} \qquad (2)$$

where sp'_{it} is the count variable representing scientific productivity as either number of publications (Pub_{it}), or number of citations to these publications in the first 5 years following publication ($Cit5YR_{it}$), of researcher i in year t. M_{it} is the mobility measure, X_{it} is a set of explanatory variables including the researcher's personal and academic characteristics (*pf*, *pt*), and institution and field effects (*h*). c_i is an individual time-invariant unobserved effect that includes ability and attitude, τ_t is the time fixed effect, and υ_{it} other time-variant unobserved effects.

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

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

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

$$sp'stock_{it} = sp'_{it-1} + (1-\delta)sp'stock_{it-1} \qquad (3)$$

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

3.4 Variables

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

The main explanatory variables in the regression refer to the mobility event. To measure the potential performance difference between pre- and post-mobility periods, we introduce two dummies that measure the mobility event: (1) $PostMob_{it}$, which switches from zero to 1 in the year of first mobility, clearly indicating the pre- and post-mobility periods; and (2) Mob_{it} which takes the value 1 only in the year of the move, indicating a one-time shock. Since our main focus is on mobility between UK universities, we run additional models for moves between UK universities ($PostUNIMob_{it}$, $UNIMob_{it}$) that exclude all researchers with international mobility experience.

[TABLE 1 ABOUT HERE]

[15] Depreciation rates of 15% and 30% return similar results.

We argued above that mobility is affected by the reputation of the sending and receiving institutions. Therefore, we use additional measures for mobility that consider the nature of transition: (1) *Upward Mobility* ($PostUP_{it}$, UP_{it}) defining a move to a higher ranked university, and (2) *Downward mobility* ($PostDOWN_{it}$, $DOWN_{it}$) defining a move to a less prestigious university.

To address the issue of industry experience with regard to mobility as discussed above we run an additional regression that considers mobility from industry ($PostIndmob_{it}$ $Indmob_{it}$) and measures a transition from industry back to academia.

As controls we include the academic's age (AGE_{it}) to account for potential life-cycle effects (Levin and Stephan 1991), and gender ($FEMALE_i$). We control also for the researcher's academic rank. The UK university system has some minimum requirements for consideration for promotion. Thus, less senior academics should have a greater incentive to publish, while professors, because of their access to research assistance and funding, may achieve higher publication rates. We consider three levels of seniority in our analysis: Lecturer or Research Fellow before first promotion ($RANK1_{it-1}$), senior position or rank after first promotion ($RANK2_{it-1}$), and professorship ($RANK3_{it-1}$). We also include an indicator for postdoctoral research experience ($POSTDOC_i$). To account for the researcher's commercial orientation (Crespi et al. 2011) we include patent stock ($PATENT_{it-1}$) which counts the number of patents filed in previous years. To account for any potential department effects related to access to resources and networks, we include the university's rank in *t-1* as defined in section 3.2 ($UniRanking_{it-1}$), in the set of regressions that consider only UK institutions. We can also expect a 'London' effect due to proximity to funding bodies and networks that might positively affect research output ($London_{it-1}$). We include subject dummies to control for discipline effects, and year dummies to control for time effects. A summary of the main variables used in the regressions is provided in Table 1, while Table 2 presents the descriptive statistics.

[TABLE 2 ABOUT HERE]

4. Results

We estimate pooled negative binomial regressions. Standard errors are clustered at the individual level and robust to heteroskedasticity and serial correlation. Table 3 shows the results for all (including international) mobility between universities (columns 1 to 4) and the results for mobility between UK universities (excluding internationally mobile academics; columns 5 to 8).

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

[*TABLE 3 ABOUT HERE*]

4.1. Job-to-job mobility

In Table 3 columns 1 to 4 which show the results for all (including international) mobility between higher education institutions, the number of observations is 1,850 in column 1, reducing to 1,673 in column 2 due to longer lags which require a minimum of four observation years, i.e. consider only academics whose careers began before 2002.

Column 1 shows publication performance changes after the mobility event. The mobility variable is positive but insignificant, indicating that academics do not perform significantly better after mobility.[16] Column 2 which presents the yearly effects of the mobility shock, shows some evidence of a short-term albeit insignificant negative effect. The results are similar for citations weighted output (columns 3 and 4).

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

To introduce our ranking measure, *PR*, which takes account of the university department quality, we consider only mobility between UK universities (Table 3, columns 5 to 8). We include researchers who were born abroad but have moved only within the UK, but exclude all researchers that moved internationally since it is not possible to produce a 23-year field-specific ranking that includes non-UK organizations. The number of observations reduces to 1,579 in column 5, and 1,424 in column 6.

Column 5 shows how publication performance changes after the mobility event. The mobility variable is positive, indicating that mobile academics perform better than non-mobile academics after mobility, but that the effect is insignificant. In column 6 which presents the

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

effects of the mobility shock, the post mobility variable remains insignificant. As in column 2, there are indications of a weakly significant negative short-term effect of mobility. The results are similar but not significant for the citation weighted output (columns 7 and 8). Overall these results show that mobile academics do not outperform non-mobile academics, and provide weak support for our hypothesis of an initial negative effect following mobility.

[*TABLE 4 ABOUT HERE*]

4.2 Social mobility

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

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

Table 4 columns 5 to 8 report the results for downward mobility (*DOWN*). They show that downward mobile researchers have lower publication productivity than their non-mobile peers, or colleagues who moved to a higher ranked institution. This effect persists after isolating the short-term effect in column 6. The negative signs are confirmed for the quality adjusted publication measure (columns 7 and 8).[17] Interestingly, in contrast to the case of upward mobility, for downward mobile researchers we find a positive short term effect of mobility in both the publications and the citations equations. The effect is strongly significant for citation weighted output, suggesting that academics benefit from a delayed positive effect of their publication pipeline which diminishes quickly. Thus, the results for downward mobility are generally associated with reduced productivity - possibly due to reduced resources. For the majority (all but 4) of researchers who moved to a lower ranked university, the job change involved a promotion, and thus, potentially more resources. However, the negative effect indicates that lower ranked institutions do not offer better packages which might compensate for loss of institutional prestige and departmental colleagues.

For the department quality measure (*UniRanking*), we find an additional positive effect for citations. This indicates that researchers moving to a lower quality institution but joining a department of recognized high quality may perform better than their counterparts who move to a low quality department.

To summarize, we find no evidence for an overall positive effect of mobility but we find that the mobility effect is conditioned by the nature of the job transition. The econometric analysis provides some evidence supporting a positive effect of upward mobility, and some evidence of a negative effect of downward mobility. We also found evidence that academic job mobility is most often associated with a short-term decrease in research performance

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

especially in the case of upward mobile researchers.

[*TABLE 5 ABOUT HERE*]

4.3 Inter-sector mobility

Table 5 reports the results for mobility from industry to academia. The regressions include all researchers including those that moved between universities. Columns 1 and 2 include all observations, and columns 3 and 4 include only those observations years when the researcher is working in academia. The number of observations is 2,367 in column 1 and 2,151 in column 3.

We find no significant effect of mobility from industry (*PostIndMob*) on research productivity. Researchers that join academia from industry (*IndMob*) publish significantly less than their peers during the first two years after the move (column 2). This initial negative effect turns positive in year three, although the effect is insignificant. Thus, while industry researchers may suffer some adaptation costs for a readjustment period related to joining academia, they benefit from increased human capital acquired during their time in industry, and in the medium term publish as much as researchers that never move out of academia. The results are confirmed in columns 3 and 4 which exclude observations during the years spent in industry. The results are similar for citation counts (columns 5 to 8). We find an initial negative effect which may turn positive in later years; however, the effects remain insignificant. Thus, we find evidence that researchers who move to academia from industry do not produce lower quality publications compared to pure academic scientists.

4.5 Control variables

The coefficients of the non-mobility control variables vary slightly across the different mobility measures and lags. We report their results in column 5, which controls also for university ranking. Age is not significantly correlated with publications but has an inverted U-shaped effect on the quality adjusted number of publications. Thus, while the number of publications does not change significantly over the life-cycle, the quality of publications increases in the first few years of the researcher's career and then declines after around the age of 40. We do not find a significant gender effect which is in line with Crespi et al.'s (2011) findings for the same sample of researchers. Patent stock is negative but insignificant in all the estimations, confirming Crespi et al. (2011).

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

The effect of mobility could be mediated by the academic position, and promotion may result in other types of benefits that directly affect performance. According to the rank indicators in the regression seniority does not affect publication outcomes significantly (see Table 3). Senior academic staff are not expected to publish more than researchers in the category *RANK 1*.

University ranking (*PR*) has no significant effect on publication numbers. However, we find a strong positive sign for the quality adjusted measure. Thus, researchers in the most prestigious institutions may not produce more but may produce better quality publications and achieve more visibility than their peers in lower ranked institutions.

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

5. Conclusions

We approach the study of mobility by assuming that in order to properly analyze the effect of mobility in the current research system it is necessary to consider different types mobility events, and short and medium to long-term return opportunities and not just to consider mobility as a one-time, one-way process.

The theoretical framework based on the job-matching approach for academics, emphasizes research and reputation aspects and allowed us to formulate different expectations regarding the short and medium-term effects of the job mobility of permanent academic staff on their productivity across different mobility types – social and intersectoral.

We applied our framework to a sample of 171 UK academic researchers in the period 1957 to 2005. Based on this sample, which should not be biased towards mobility, we found a high level of job mobility: two-thirds of researchers changed jobs at least once, and one-third were involved in two job moves. Analysis of the difference in performance between mobile and non-mobile researchers showed a positive although insignificant overall effect of mobility, and a negative weakly significant short-term effect. When considering mobility to a better, or a worse department than the department of origin, we found that mobility to a higher ranked university has a weakly positive impact on publication output but not citations, while downward mobility tends to decrease the researcher's overall research performance. We found evidence of decreased productivity in the years after a job change - probably or most likely due to adjustment costs for all types of job changes with the exception of downward mobility. Downward mobile researchers may benefit from their preexisting publication pipeline on joining the new department, resulting in a short-term positive effect. However, their performance drops significantly in later years. Thus, hiring researchers from top-departments might be a short-term strategy for lower ranked departments to improve their visibility, with negative medium to long-term productivity pay-offs for mobile researchers. These results partially confirm the findings in Allison and Long (1990) which finds a publication increase associated with a move to a higher ranked department, and a performance decrease associated with a move downwards.

The analysis of inter-sector mobility shows that the performance of researchers that moved to academia from industry does not differ significantly from that of purely academic researchers. Researchers coming from industry suffer short-term mobility costs but they appear to adapt quickly in terms of research performance. However, we need to take into account that the industry experience of most of the researchers in our sample was in large company laboratories that would have supported their research activity. While Dietz and Bozeman (2005) find a positive effect of industry experience on patent counts, in the case of publication counts we found no effect of industry experience. Finally, we found evidence that temporary research positions, in our case either postdoc positions or short term Research Fellow contracts, which have increased in frequency in recent years (Stephan 2012), have a long-term negative effect on research performance which perhaps should be of concern to policy makers and academia.

These results indicate that policies encouraging the mobility of researchers should be refined to take account of different mobility events and short-term and long-term consequences. Mobility per se appears not to have clear positive effects on the scientific productivity of the researchers. On the contrary, it has clear short-term negative effects probably associated with mobility costs. Job mobility to a higher quality department increases publication performance. This could indicate that policies encouraging mobility might unintentionally exacerbate the dynamics of an unequal individual and institutional distribution of scientific performance that favors the current winners. The negative effects of downward mobility on academic performance suggests the need for additional institutional measures to ensure the high performance of individual researchers who move to lower quality departments to avoid that mobility decisions resulting in individual and institutional quality mismatches.

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Tables

Table 1. Dimensions and variables of mobility

Job-to-job mobility (change of employer)	***Inter-sector mobility***	***Social mobility*** (change in social position)
$PostMob_{it}$ Mob_{it} $PostUNIMob_{it}$ $UNIMob_{it}$	$Indmob_{it}$ $PostIndmob_{it-1}$	Upward Mob $PostUP_{it}$ Downward Mob $PostDOWN_{it}$

Table 2: Definition and Summary Statistics of variables used in the regression. 1982-2005

		Full Sample of 2367 observations				HE Sample of 1850 observations				Reduced Sample of UK-HEI 1579 observations			
VARIABLES	Definition	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Dependent Variable													
PUB$_{it}$	Number of publications in *t*	4.77	6.31	0.0	97	5.19	6.80	0.0	97	5.52	7.24	0.0	97
CIT5YR$_{it}$	Number of citations in *t* to *t+5* to publications in *t*	63.33	100.94	0.0	1122	70.78	108.24	0.0	1122	75.37	113.55	0.0	1122
Mobility Variable													
PostMOB$_{it}$	Moved at least once between HEI before *t*	0.40	0.49	0.0	1	0.33	0.47	0.0	1				
MOB$_{it}$	Moved between HEI in *t*	0.05	0.21	0.0	1	0.04	0.20	0.0	1				
PostINDMOB$_{it}$	Moved at least once from industry to HEI before *t*	0.13	0.33	0.0	1								
INDMOB$_{it}$	Moved from industry to HEI in *t*	0.01	0.10	0.0	1								
PostUNIMOB$_{it}$	Moved at least once between UK HEI before *t*									0.27	0.44	0.0	1
UNIMOB$_{it}$	Moved between UK HEI in *t*									0.03	0.18	0.0	1
PostUP$_{it}$	Moved upward at least once before *t*									0.10	0.30	0.0	1
UP$_{it}$	Moved upward in *t*									0.01	0.11	0.0	1
PostDOWN$_{it}$	Moved downward at least once before *t*									0.12	0.33	0.0	1
DOWN$_{it}$	Moved downward in *t*									0.01	0.11	0.0	1
Feedback measures													
Pre-sample average$_{i}$ (PUB)		0.62	0.65	0.0	3	0.70	0.67	0.0	3	0.76	0.66	0.0	3
Stock$_{it-1}$ (PUB)		25.58	33.07	0.0	439	27.65	35.34	0.0	439	29.36	37.49	0.0	439
Pre-sample average$_{i}$ (CIT)		8.50	13.22	0.0	75	9.50	14.39	0.0	75	10.22	14.12	0.0	69
Stock$_{it-1}$ (CIT)		323.68	481.42	0.0	5499	358.12	517.91	0.0	5499	376.34	544.55	0.0	5499
Control Variables													
AGE$_{it}$	Age in *t*	43.27	10.15	25.0	77	43.46	10.34	25.0	77	43.58	10.46	26.0	77
FEMALE$_{i}$	Dummy = 1 if female	0.11	0.31	0.0	1	0.11	0.31	0.0	1	0.10	0.31	0.0	1
FIRM$_{it-1}$	Working in Industry in *t-1*	0.09	0.29	0.0	1								
RANK1$_{it-1}$	Lecturer or Research Fellow in *t-1*	0.28	0.45	0.0	1	0.33	0.47	0.0	1	0.33	0.47	0.0	1
RANK2$_{it-1}$	Senior position in *t-1*	0.33	0.47	0.0	1	0.33	0.47	0.0	1	0.35	0.48	0.0	1
RANK3$_{it-1}$	Professor in *t-1*	0.30	0.46	0.0	1	0.34	0.47	0.0	1	0.32	0.47	0.0	1
POSTDOC$_{i}$	Dummy = 1 if postdoc before first position	0.44	0.50	0.0	1	0.50	0.50	0.0	1	0.53	0.50	0.0	1
PATENT$_{it-1}$	Stock of patents up to t-1	1.03	3.25	0.0	25	0.95	3.11	0.0	25	1.11	3.34	0.0	25
UNIRANKING$_{it-1}$	Percentile Ranks (*PR*) of UK HEI in *t-1*									0.31	0.32	0.0	1
LONDON$_{it-1}$	Dummy = 1 if working in London in *t-1*	0.14	0.34	0.0	1	0.13	0.33	0.0	1	0.12	0.32	0.0	1
CHEMISTRY$_{i}$	Chemistry	0.39	0.49	0.0	1	0.47	0.50	0.0	1	0.51	0.50	0.0	1
PHYSICS$_{i}$	Physics	0.34	0.48	0.0	1	0.30	0.46	0.0	1	0.29	0.45	0.0	1
COMPUTER$_{i}$	Computer Science	0.13	0.33	0.0	1	0.11	0.32	0.0	1	0.09	0.29	0.0	1
MECHANICAL$_{i}$	Mechanical Engineering	0.14	0.35	0.0	1	0.12	0.33	0.0	1	0.11	0.31	0.0	1

TABLE 3: Effect of mobility between HEI on publication performance.

	Mobility between HEI				Mobility between UK-HEI			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	PUB	PUB	CIT5YR	CIT5YR	PUB	PUB	CIT5YR	CIT5YR
Pre-sample Average (PUB/CIT)	0.115**	0.120**	0.005*	0.002	0.109*	0.117*	0.004	0.002
	(0.054)	(0.056)	(0.003)	(0.003)	(0.061)	(0.063)	(0.003)	(0.003)
Stock (PUB/CIT)	0.013***	0.013***	0.001***	0.001***	0.013***	0.013***	0.001***	0.001***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)
$PostMob_{it}$ / $PostUnimob_{it}$	0.088	0.073	0.105	0.104	0.114	0.130	0.126	0.133
	(0.069)	(0.069)	(0.096)	(0.092)	(0.086)	(0.087)	(0.111)	(0.109)
L. Mob_{it} / L.$UniMob_{it}$		-0.159		-0.011		-0.220*		0.012
		(0.097)		(0.154)		(0.115)		(0.196)
L2. Mob_{it} / L2.$UniMob_{it}$		0.009		0.050		-0.075		-0.012
		(0.089)		(0.124)		(0.093)		(0.138)
L3. Mob_{it} / L3.$UniMob_{it}$		-0.094		-0.185		-0.146		-0.155
		(0.107)		(0.141)		(0.122)		(0.167)
AGE_{it}	0.039	0.016	0.083*	0.069	0.036	0.006	0.089*	0.080
	(0.029)	(0.032)	(0.045)	(0.053)	(0.031)	(0.033)	(0.047)	(0.054)
AGE_{it} 2	-0.000	-0.000	-0.001**	-0.001	-0.000	-0.000	-0.001**	-0.001*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
$FEMALE_i$	0.146	0.004	0.067	-0.122	0.192	0.020	0.150	-0.092
	(0.135)	(0.096)	(0.135)	(0.134)	(0.157)	(0.113)	(0.171)	(0.166)
Reference: $RANK1_{it-1}$								
$RANK2_{it-1}$	0.089	0.078	-0.086	-0.061	0.106	0.094	-0.036	-0.020
	(0.076)	(0.073)	(0.131)	(0.130)	(0.084)	(0.081)	(0.142)	(0.143)
$RANK3_{it-1}$	0.070	0.062	-0.101	-0.083	0.144	0.136	0.002	-0.009
	(0.107)	(0.106)	(0.163)	(0.163)	(0.130)	(0.125)	(0.184)	(0.187)
$POSTDOC_i$	-0.133	-0.071	-0.017	0.059	-0.186*	-0.108	-0.017	0.092
	(0.090)	(0.082)	(0.110)	(0.109)	(0.103)	(0.092)	(0.125)	(0.124)
$PATENT_{it-1}$	-0.003	-0.001	-0.002	-0.002	-0.003	-0.000	-0.004	-0.004
	(0.007)	(0.007)	(0.010)	(0.009)	(0.008)	(0.007)	(0.013)	(0.011)
$UniRanking_{it-1}$					0.053	0.079	0.311**	0.287*
					(0.107)	(0.113)	(0.144)	(0.158)
$LONDON_{it-1}$	-0.112	-0.062	-0.221	-0.211	-0.074	-0.057	-0.193	-0.225
	(0.117)	(0.116)	(0.164)	(0.160)	(0.141)	(0.133)	(0.199)	(0.189)
Reference: $CHEMISTRY_i$								
$PHYSICS_i$	-0.075	-0.083	-0.127	-0.140	-0.063	-0.074	-0.157	-0.173
	(0.082)	(0.077)	(0.119)	(0.123)	(0.088)	(0.084)	(0.133)	(0.139)
$COMPUTER_i$	-0.953***	-0.839***	-1.742***	-1.732***	-1.133***	-0.961***	-1.860***	-1.797***
	(0.154)	(0.138)	(0.233)	(0.235)	(0.197)	(0.179)	(0.292)	(0.298)
$MECHANICAL_i$	-0.601***	-0.556***	-1.240***	-1.247***	-0.640***	-0.582***	-1.320***	-1.331***
	(0.172)	(0.161)	(0.221)	(0.210)	(0.215)	(0.202)	(0.255)	(0.235)
Constant	0.642	1.173	2.258**	2.556**	0.798	1.453*	2.086**	2.235*
	(0.670)	(0.750)	(0.999)	(1.208)	(0.711)	(0.768)	(1.053)	(1.239)
lnalpha	-1.208***	-1.366***	0.392***	0.305***	-1.174***	-1.337***	0.362***	0.273***
log Likelihood	-4436.187	-4062.195	-8847.143	-8113.580	-3855.741	-3523.254	-7651.487	-6999.140
Observations	1850	1673	1850	1673	1579	1424	1579	1424
Clusters	124	122	124	122	108	106	108	106

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

TABLE 4: Effect of upward and downward mobility between UK-HEI on publication performance

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

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

Note: The results hold if we include upward and downward mobility in the same regression model. Results are also robust if we exclude other mobile researchers and compare upward (downward) mobility only to immobile peers.

TABLE 5: Effect of Industry to HEI-mobility on publication performance.

VARIABLES	(1) NBREG PUB	(2) NBREG PUB	(3) NBREG PUB	(4) NBREG PUB	(5) NBREG CIT5YR	(6) NBREG CIT5YR	(7) NBREG CIT5YR	(8) NBREG CIT5YR
Pre-sample Average (PUB/CIT)	0.125***	0.133**	0.123**	0.129**	0.007**	0.004	0.005**	0.003
	(0.047)	(0.052)	(0.049)	(0.053)	(0.003)	(0.004)	(0.003)	(0.003)
Stock (PUB/CIT)	0.014***	0.014***	0.014***	0.013***	0.001***	0.001***	0.001***	0.001***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
$PostIndMob_{it}$	-0.058	-0.021	-0.050	-0.000	-0.015	0.047	0.027	0.109
	(0.099)	(0.104)	(0.104)	(0.109)	(0.149)	(0.157)	(0.152)	(0.163)
L. $IndMob_{it}$		-0.593***		-0.650***		-0.518		-0.597
		(0.221)		(0.222)		(0.381)		(0.394)
L2. $IndMob_{it}$		-0.266		-0.311*		-0.071		-0.160
		(0.164)		(0.163)		(0.265)		(0.268)
L3. $IndMob_{it}$		0.240		0.203		0.022		-0.070
		(0.182)		(0.174)		(0.301)		(0.272)
AGE_{it}	0.058**	0.039	0.051*	0.027	0.074	0.071	0.089**	0.067
	(0.028)	(0.030)	(0.028)	(0.030)	(0.046)	(0.052)	(0.043)	(0.050)
AGE_{it} 2	-0.001**	-0.000	-0.001**	-0.000	-0.001*	-0.001	-0.001**	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
$FEMALE_i$	0.045	-0.086	0.110	-0.020	-0.074	-0.250	-0.009	-0.172
	(0.124)	(0.099)	(0.126)	(0.099)	(0.152)	(0.161)	(0.147)	(0.158)
Reference:	$FIRM_{it-1}$	$FIRM_{it-1}$	$RANK1_{it-1}$	$RANK1_{it-1}$	$FIRM_{it-1}$	$FIRM_{it-1}$	$RANK1_{it-1}$	$RANK1_{it-1}$
$RANK1_{it-1}$	0.339**	0.342**			0.435*	0.469*		
	(0.160)	(0.157)			(0.245)	(0.245)		
$RANK2_{it-1}$	0.407***	0.401***	0.092	0.081	0.344	0.387*	-0.095	-0.067
	(0.146)	(0.147)	(0.077)	(0.073)	(0.227)	(0.228)	(0.127)	(0.128)
$RANK3_{it-1}$	0.334**	0.321*	0.045	0.032	0.360	0.396	-0.062	-0.029
	(0.165)	(0.165)	(0.104)	(0.103)	(0.256)	(0.259)	(0.158)	(0.159)
$POSTDOC_i$	-0.112	-0.057	-0.117	-0.065	-0.036	0.042	-0.041	0.030
	(0.079)	(0.072)	(0.081)	(0.074)	(0.105)	(0.107)	(0.106)	(0.107)
$PATENT_{it-1}$	-0.013	-0.010	-0.007	-0.004	-0.020	-0.019	-0.009	-0.007
	(0.011)	(0.010)	(0.008)	(0.007)	(0.019)	(0.019)	(0.011)	(0.010)
$LONDON_{it-1}$	-0.081	-0.041	-0.071	-0.032	-0.180	-0.170	-0.171	-0.162
	(0.103)	(0.103)	(0.103)	(0.103)	(0.129)	(0.127)	(0.130)	(0.127)
Reference: $CHEMISTRY_i$								
$PHYSICS_i$	-0.079	-0.078	-0.081	-0.082	-0.093	-0.090	-0.144	-0.145
	(0.076)	(0.071)	(0.077)	(0.071)	(0.110)	(0.112)	(0.107)	(0.109)
$COMPUTER_i$	-1.016***	-0.911***	-0.956***	-0.855***	-1.846***	-1.830***	-1.813***	-1.782***
	(0.149)	(0.132)	(0.152)	(0.137)	(0.201)	(0.202)	(0.207)	(0.208)
$MECHANICAL_i$	-0.499***	-0.469***	-0.499***	-0.464***	-1.089***	-1.116***	-1.172***	-1.175***
	(0.152)	(0.143)	(0.147)	(0.139)	(0.203)	(0.195)	(0.194)	(0.187)
Constant	-0.191	0.247	0.343	0.869	1.890*	1.944	2.123**	2.617**
	(0.675)	(0.697)	(0.644)	(0.712)	(1.098)	(1.207)	(0.969)	(1.143)
lnalpha	-1.108***	-1.251***	-1.146***	-1.292***	0.524***	0.443***	0.446***	0.368***
log Likelihood	-5533.131	-5109.331	-5121.162	-4735.606	-10931.544	-10116.790	-10142.350	-9401.899
Observations	2367	2161	2151	1970	2367	2161	2151	1970
Clusters	150	148	149	147	150	148	149	147

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

Note: Results are robust if we also include mobility between universities to this model.