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International Careers of Researchers in Biomedical Sciences: A Comparison of the US and the UK

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Abstract

This chapter analyses the mobility of academic biomedical researchers in the US and the UK. Both countries are at the forefront of research in biomedicine, and able to attract promising researchers from other countries as well as fostering mobility between the US and the UK. Using a database of 292 UK based academics and 327 US based academics covering the period 1956 to 2012, the descriptive analysis shows a high level of international mobility at education level (BA, PhD and Postdoc) with small, but significant transatlantic exchanges, and shows high levels of cross-border mobility amongst senior academics based in the UK. There is a high level of career mobility with 50% of the sample having changed jobs at least once, and 40% having moved within academia. There is no significant difference in job-job mobility between the two countries although there are some interesting institutional differences concerning international and cross-sector mobility. The empirical analysis focuses on the importance of postdoctoral training in the US and the UK. The results indicate that working in the US is correlated to higher researcher performance in terms of both publication numbers and impact/quality adjusted publications (in top journals and average impact). The publications of researchers with postdoctoral experience are generally of a higher average impact. This applies especially to postdoc experience at top-quality US institutions although a postdoc at a UK top institution is associated with higher top journal publications and higher average impact. In relation to the UK sample, we find that a US postdoc (especially in a top institution) is correlated to subsequent performance in the UK academic market. Finally, we see that US postdocs that stay in the US publish more and publications with higher impact/quality than those that move to the UK; however, these effects are stronger for those who studied for their PhD degree outside the US. Therefore, we find some evidence that the US is able to retain high performing incoming PhD graduates.

Keywords: International mobility; academic career; academic labor market; research productivity; postdoc; biomedical

JEL: O31, I23, J24

1. Introduction

In the last 30 years, biomedical sciences have become a fundamental area of research in national scientific research portfolios (Adams, 1998; Glover et al., 2014). Despite increased scientific production in countries in Asia and continental Europe, the US and the UK remain the leaders of the field (Wu, 2004; Webster, 2005; Glanzel, et al. 2008; Hu and Rousseau, 2009; BIS, 2013[1]). For example, in a comparison of ten countries, the scientific production of the UK and the US show the highest averages for normalized citation rates for the period 1996 to 2006 (Hu and Rousseau, 2009).[2]

Biomedical sciences, like other scientific fields (OECD, 2008; Auriol et al., 2013), are characterized by increased internationalization of their human resources and collaboration patterns (NIH, 2012). In the US, foreign citizens represent an important part of the biomedical science work force (Stephan, 2012) and their share has increased more rapidly compared to the share of nationals (NIH, 2012). Growing internationalization is evident at all research levels starting from PhD students and postdocs to full professor in the US, and similar trends are observed in the UK (BIS, 2013; Sastry, 2005).

The world's top researchers tend to move (e.g. as undergraduate students, PhD students, post-doctoral researchers or workers with permanent contracts) to countries with strong research systems, with the result that their mobility is an indication of the attractiveness of a country

[1] Webster et al., (2003) showed the strength of the UK as the second highest producer of papers in the field of biomedicine, but noted also that Japan overtook the UK in terms of number of articles in the latest years of the period analyzed (1989-2002). BIS (2013) gives further support for the strength of the UK and US in the field, especially in terms of citation impact. Still, it also reports an increased performance in emerging science markets (especially China, which moves to second place behind the US in terms of article numbers), resulting in a slight decline of overall importance (based on world article share) of the US and the UK in the period 2002 to 2012. Both still dominate in terms of field weighted citation impact which increases during the same period.

[2] These are: the US, UK, France, Germany, Italy, Japan, South Korea, China, Singapore and India.

(Hunter et al., 2009) or institution (Oyer, 2007). Despite the importance of this globally mobile workforce, we have little information on the role of foreign-trained and other types of mobile researches since they are not accounted for systematically across different researcher populations (NIH, 2012; Ghaffarzadegan, et al., 2013).

The US and the UK show similarities and differences in their academic markets. Both academic systems are highly international (Ziman, 1991; NIH, 2012; BIS, 2013) and competitive (Stephan, 2012). Students do not tend to join the staff in their degree awarding institution after completing their PhD research, in either the US[3] or the UK (Navarro and Rivero, 2001; Horta et al, 2010). The promotion system, the race for positions at the most prestigious institutions (Hoare, 1994) and other systems of evaluation, such as the Research Evaluation Framework (REF), make the UK academic system more competitive than other academic systems in Europe. In the US, academic salaries vary more than in the UK where there is a higher level of standardization in salary scales, although salary diversification has increased substantially since the early 2000s.

In this context, this chapter studies the relationship between mobility patterns and academic performance with particular attention to international (transatlantic) mobility, for a sample of 619 US and UK biomedical researchers (327 from the US and 292 from the UK). We carry out a descriptive analysis of labor markets of these countries, paying particular attention to their mobility patterns, and we assess whether postdoctoral stays grant a performance premium, considering international and educational mobility patterns. The BIOMEDMOB database, built from CV information, includes detailed personal information, employment

[3] Although some inter-elite inbreeding might occur in the US (see Burris, 2004; Eisenberg and Wells, 2000) and possibly also in the UK.

patterns and publishing activities of mobile and immobile researchers for the period 1956 to 2012.

The two samples analyzed are quite similar in terms of mobility patterns, once country specificities are considered. We find that US-based researchers achieve higher performance than UK-based researchers, however the gap between the two has narrowed. US postdoctoral training implies a quality premium for researchers' performance, which is highest for those that completed a postdoc at a top US institution. We also find that this US postdoc premium transfers geographically, that is, researchers working in the UK having completed a US postdoc (especially at a top institution) publish in journals with higher average impact. We also find some evidence that the US is able to not only attract top researchers worldwide at postdoctoral and tenure level, and give them research advantages, but is also able to retain the best researchers who go to the US for their postdoctoral training.

The chapter is structured as follows. Section 2 analyses mobility patterns in biomedical science; Section 3 discusses the theoretical background and presents the hypothesis. Section 4 presents the BIOMEDMOB dataset and a descriptive analysis of career and mobility. Section 5 reports the econometric results and Section 6 concludes the chapter.

2. Careers and mobility in biomedical science

Scientists tend to move internationally to countries with strong research systems (Freeman, 2006; OECD, 2008; Weinberg, 2009). In the US, the number of international students – mostly undergraduates - has increased by 32% since 2000-2001 (Institute of International Education, 2012). The trend is similar in the UK making it the country with the largest populations of foreign PhD students in Europe. For instance, in 2012, 47% of PhD students in the UK came from abroad[4] (Eurostat, 2012).

Countries and research institutions pay attention to the inflows and outflows of the research workforce since these are measures of how effectively they are competing in the "global war for talent" (Chambers et al., 1998). The 2012 United States House of Representative legislation allows an additional 55,000 green cards for the highest qualified foreign graduates from American universities in Science, Technology Engineering and Mathematics (STEM) fields, which demonstrates the interest of the government in retaining this highly international workforce.[5]

The US and the UK are characterized by increasing internationalization of their workforce, a trend that applies especially to the biomedical field. In the 30 years 1978 and 2008 the number of PhDs in biomedical fields in the US more than tripled, from around 11,000 to more than 35,000 (FASEB, 2013). The number of doctorates awarded in biomedical fields also increased in the UK, with a threefold increase between 1994/95 to 2012/13, from 1,114 to 3,365[6]. In both countries the number of foreign doctoral students has increased significantly (the growth in EU students has been particularly important for the UK). Academic employment has also increased, but at a lower rate and in the form of non-permanent positions, encouraging young researchers to look for postdoc positions and other

[4] Only Liechtenstein (86.8%), Luxembourg (84.1%) and Switzerland (50.7%) have higher percentages in Europe (Data on the second stage of tertiary education leading to an advanced research qualification - ISCED level 6).

[5] In 2014, in the US, a proposal was put forward for a rule change that might improve opportunities for the employment of highly skilled aliens. It would offer Employment Authorization Cards (EAD) to some H4 visa holders and make it easier for outstanding foreign professors and researchers to acquire an EB-1 visa. H4 visas are issued by the US Citizenship and Immigration Services (USCIS) to immediate family members of an H-1B visa holder, which allows US employers to employ foreign workers in specialty occupations on a temporary basis

[6] HESA Students, Qualifiers and Staff data tables, https://www.hesa.ac.uk/content/view/1973/239/

employment opportunities in other sectors (NIH, 2012:25).[7] The number of postdocs in biological science[8] in the US has increased from 7,083 in 1980 to 21,537 in 2010, accounting for 34% of all postdocs in science, engineering and health in 2010 (GSS: 2013). Ghaffarzadegan, et al. (2013), using FASEB data, estimate growth in international postdocs in the field at 400% between 1985 and 2009. In the UK, the share of foreign academics in the field increased slightly from 28% in 2007/2008 to 31% in 2012/2013.[9] Foreign postdoc researchers with temporary contracts in the UK also increased in that period, from 46% to 50%.[10]

The increasing biomedical workforce, including more international workers employed on a temporary basis looking for employment in non-academic sectors, has raised policy concerns about the increasing temporariness of the biomedical workforce. The report published by the NIH (2012) highlights the increasing number of temporary contracts, and recommends reducing the duration of postdoctoral positions. Postdoctoral positions could be an opportunity for research development (Gentile et al, 1989; Levey et al, 1988; Steiner et al, 2002; Su, 2011), a solution for researchers unable to find a permanent position (Zumeta, 1985) or for those with visa restrictions (Lan, 2012).[11] However, as the NIH report suggests, the lack of information on postdocs and other mobile workforce in the field (such as foreign trained) makes it difficult to determine the effect of the increasing number of postdocs and

[7] SRD data for 2010 for the field of biology (including agriculture, environmental life sciences) shows that from a total of 83,500 employed doctoral scientists and engineers in 4-year educational institutions, 38.8% were tenured, 14.8% on tenure track and 13.5% non-tenure track (http://ncsesdata.nsf.gov/doctoratework/2010/html/SDR2010_DST20.html).
[8] We consider data on "biological sciences" for the US as this field category is more similar to the one used for the UK. "Health" fields were not included due to different categorisations in the data sources used.
[9] Extracted from HESA database, September 2014.
[10] Extracted from HESA database, September 2014.
[11] Most postdocs in the broadly defined biomedical fields are in the US on temporary visas. In 1980, 35% of all US postdocs in science, engineering, and health were in the country on temporary visas; this figure was 53% in 2010 (own calculations based on NSF data).

other changes at a systemic level.[12] To contribute to this debate, in the empirical sections of this chapter, we use individual level data on researchers' careers to investigate mobility patterns of academics based in the US or the UK, and analyze the effects of postdoctoral training on research performance. This will allow us to identify whether career paths differ between researchers in the two countries and whether postdoctoral mobility pays off in terms of research performance.

3. International mobility, career progression and research performance

Scientists tend to move to another country for research related reasons. The self-selection mechanisms that operate in the migration process[13] might also be research related which could affect their future prospects (Fernández-Zubieta et al., 2015). Ackers (2005) suggests that long-term mobile researchers could be considered "knowledge migrants" since they tend to be more interested in opportunities for career advancement than in purely economic reasons. Nerdrum and Sarpebakken (2006) point to the mobility of researchers as driven by research factors, such as keeping updated or searching for sources of inspiration, as well as "curiosity driven" (Stephan and Levin, 1992; Mahroum, 1998). These research-related factors appear to promote mobility and are found to be more important than family related issues across countries (Ivancheva, L. and Gourova, E., 2011).[14] Research-related factors appear important also for the decision to return to the country of origin (Thorn and Holm-Nielsen, 2008). However, Franzoni et al. (2012) indicate that while professional reasons are dominant

[12] Foreign trained are not accounted for systematically across research populations (students, postdocs, researchers working in academia or industry).

[13] The economic literature on the assimilation of immigrants (Chiswick, 1978; Borjas, 1985; LaLonde and Topel, 1992) suggests that there are positive self-selection effects (Chiswick, 1978), immigrants being more talented, more entrepreneurial and more risk averse. These also affect the decision of migrants to stay in a country or to return home. Analysis of the return decisions of migrants indicates that foreigners who remain in the country might be the best or the worst of the group (Borjas, 1985; Borjas and Bratsberg, 1996, Dustmann, 2003; Grogger and Hanson, 2011).

[14] The countries studied were Austria, Bulgaria, Cyprus, Czech Rep., Greece, Hungary, Slovakia and Switzerland.

for the decision to take a postdoc abroad, family-related reasons are important for explaining the return mobility of foreign scientist to their home countries.

Thus, researchers' outward mobility and return mobility are affected by research related considerations that operate through selection mechanisms and matching processes. These may differ at different career stages. A researcher (student) can enter a foreign country at various career stages: 1) education (BA, MA, PHD); 2) post-doc; and 3) job (first untenured job or senior tenured position). Research related factors that explain the decision to move might become more important as the career progresses, and may affect the research performance of researchers. Positive efficiency-enhancing effects depend on the availability of information to allow optimal matching (Jovanovich, 1979 and Mortensen, 1986).[15] In addition, specific individual and institutional selection mechanisms might operate in the case of foreign researchers, which might enhance research performance due to the increased level of information required by and about this group.

The level of information held by the researchers on the research system and the institutions (and the ability to make the right choices) differs at different career stages. A PhD student, compared to a postdoc, lacks an adequate level of information on the research system and institutional quality. Postdoctoral researchers are more experienced and can be expected to be better informed about the institutions and the advantages and opportunities available. David (1992) and Mangematin (2000) suggest that PhD students have to make choices when they have little information about their future careers. A postdoctoral-level researcher should be more able to recognize the 'invisible colleges' (Crane, 1972) and, therefore, more able to make the "right choice" in research terms.

[15] See Franzoni et al. (2014) for performance premium of migrants controlling for positive selection into migration.

Similarly, the level of research-related information that research institutions have and require about their candidates changes significantly across career stages. In the early career stage, information on research achievements is scarce, making other non-research factors or non-individual research factors, such as the quality of the BA/MA awarding institution, an important source of information for the hiring institution (Long, 1978; Baldi, 1995). However, institution-level foreign education credentials are more difficult for home institutions to differentiate, providing less added information for the selection. An institution considering hiring a postdoc, however, has to rely upon proven publication performance and other research related activities carried out during the PhD research process as more reliable source of information about the latent quality of the candidate.

Based on this reasoning of increasing availability of research-related information along the career path, and individual and institutional selection mechanisms of foreigners, we can expect that international mobility will result in a better match (in terms of future performance) at a postdoctoral level compared to PhD level.

Postdoctoral research training can be either a stepping-stone in a scientific career or a sign of “job queuing” for a better position, risking the scientist losing momentum (Zumeta, 1985; NRC, 2012). There is some evidence that a post-doc improves academic performance (Meng and Su, 2010; Su, 2011) and the scientific impact of the individual’s work (McGuinnis et al., 1982). There is evidence also that foreigners are more productive than their native US peers (Stephan and Levin, 2007; Corley and Sabharwal, 2007; Lee, 2004). Taking this evidence together might suggest that the effect of going to a leading scientific country to undertake a postdoc will have a positive effect on academic performance. However, foreign nationals appear also to be more likely to undertake postdoctoral positions because of the poor availability of other employment opportunities (Corley and Sabharwal, 2007), thereby increasing the length of their postdoctoral period (Stephan and Ma, 2005). Also, researchers that undertake a postdoc in a foreign leading scientific country appear to have important research advantages (due to selection processes and high motivation) that allow them to benefit more from a postdoctoral stay in terms of research performance, but also risk the disadvantage of precarious research markets which could then diminish these research advantages. Studies of the academic job market show also that the quality of the institution providing the training affects the institutional selection process and influences future career performance (McGuinnis et al., 1982; Long, 1978). Being trained at a top-quality institution might grant postdocs additional research advantages which, in the case of foreign nationals, might help to overcome the disadvantages and lead to a successful stay in terms of academic performance.

4. Data description

Our sample is drawn from researchers (Principal Investigators (PI) and/or Co- Investigators (CO-I)) that received funding from the two most important public funding agencies for biomedicine in each country: the Biotechnology and Biological Sciences Research Council (BBSRC) in the UK and the National Institute of Health (NIH) in the US. This sample frame allows us to identify research active academic scientists in biomedical fields although it might exclude scientists who are funded exclusively by private foundations. Annex 1 provides a description of the data construction and response analysis.

CVs are collected from researchers' websites and by email, and used to construct the careers of our sample of biomedical scientists. CVs were coded by hand. Personal details, education history and career paths up to 2012 were recorded. We excluded academics with incomplete career data, those who had retired within the five years prior to 2012, and those who had not achieved a permanent academic position by 2012. We also excluded researchers with medical degrees since they face a very different labor market.[16] The final version of the BIOMEDMOB database, which includes only comparable researchers in the UK and the US for which we have complete career and publication information, comprises 292 UK and 327 US-funded academics for the period 1956 to 2012. In the following, we present the descriptive statistics for our final sample of 619 researchers relating to basic demographic information, careers and mobility. We compare the UK and the US samples, highlighting similarities and a few interesting differences.

Basic Demographic Information

A total of 22% of researchers in the sample are women; the average age is 53 in 2012; 77% are US or UK citizens; 81% studied for a US or UK undergraduate degree; 86% were awarded a PhD degree by a US or UK institution (average year of BA award is 1980 and PhD 1985). The average researcher was appointed to a first academic position (tenure or tenure-track) in 1990.

Table 1: demographic information (in year 2012 or last year in data)

	UK				US				
	mean	Sd	min	Max	mean	Sd	Min	Max	Mean Diff
Female	0.22	0.41	0	1	0.22	0.41	0	1	ns
Age in 2012[1]	51.97	8.40	35	71	54.60	10.84	37	89	***
Born in the UK[2]	0.77	0.29	0	1					
Born in the US[2]					0.77	0.42	0	1	ns[4]
BA in the UK[3]	0.83	0.38	0	1					
BA in the US[3]					0.78	0.41	0	1	ns[4]
PhD in the UK[1]	0.83	0.37	0	1					
PhD in the US[1]					0.89	0.31	0	1	*[4]
Year BA[3]	1981.78	8.68	1962	1999	1979.39	10.90	1943	1997	***
Year PhD[1]	1986.54	9.07	1967	2006	1985.68	11.36	1950	2004	ns
Year start career	1991.49	9.93	1968	2011	1989.01	11.92	1956	2008	***
N	292				327				

*** p<0.01, ** p<0.05, * p<0.1
[1] Age is missing for 9 and PhD for 6 academics. [2] Country of Birth is only known for 372 academics (186 UK & 186 US). [3] BA information is missing for 19 academics. [4] Compared to row above.

[16] This exclusion is also necessary to make the BBSRC and NIH samples more comparable since the former is less likely to include medical doctors.

There are some differences between the US and the UK samples. Table 1 presents the basic demographic information. Researchers in the US are 2.65 years older, completed their BA and entered their first academic job approximately 2.5 years earlier. However, if we consider three years as the time period for an academic cohort, we can claim that the two samples are not significantly different. The statistics show that most academics working in the UK and US were previously educated there at undergraduate and PhD levels, with a slightly higher share for the US at PhD level. Country of birth is available only for 372 researchers; in this smaller sample, the share of foreigners is similar for both countries.

Table 2 Country of BA and PhD across UK-US sample

Sample		BA				PhD			
		UK	US	Other	Total	UK	US	Other	Total
UK	N	226	7	40	273	236	17	30	283
	%	82.8	2.6	14.6	100	83.4	6.0	10.6	100
US	N	11	249	57	317	14	283	22	319
	%	3.5	78.5	18	100	4.4	88.7	6.9	100

Table 2 analyzes countries of BA and PhD education in more detail. We are interested in particular in US-UK educational mobility. Approximately 17% of the UK sample moved to the UK from abroad for their undergraduate education while the same share is 21% in the case of the US. Only 2.6% of academics working in the UK obtained their BA in the US; similarly 3.5% of researchers working in the US completed their BA in the UK. The share of researchers with foreign PhD education is similar to that with BA education in the case of the UK, but lower for the US, with only 11% of researchers working in the US having completed their PhD abroad. Transatlantic PhD education mobility is higher, with US-to-UK mobility reaching 6% and UK-to-US mobility 4.4%. The composition of the category "Other" shows important differences across samples, with prominent countries of undergraduate degree being Germany (14.9%), Australia (12.8%) Canada (8.5%) and New Zealand (8.5%) in the

UK sample, and China (18.5%), Canada (12.3%), India (9.2%) and Germany (7.7%) in the US sample. PhD level education shows a high concentration in terms of degree awarding countries, with the US accounting for 35% of foreign PhDs in the UK sample and UK accounting for 37% of foreign PhDs in the US sample, followed by Australia, Germany and the Netherlands with about 8% respectively in the UK and by Germany (11.4%), Canada (8.6%) and Switzerland (8.6%) in the US.

Postdoc mobility

Table 3 presents detailed comparative information on academic mobility. All variables are dummies except for the number of job-job changes which has a maximum value of 4 in the UK sample and 6 in the US sample with a mean of 0.78 for both countries. On completion of their PhD studies, 81% of researchers did a postdoc[17]. In both systems postdocs are very prevalent, with 84% of researchers in the UK and 80% of researchers in the US, respectively. UK academics are more likely to have done their postdoc abroad with 41% completing a postdoc in the US or some other country, against 11% having completed a postdoc abroad in the case of the US. The main postdoc country for UK-based scientists is the US with 26% of the total UK sample having completed a postdoc there, while only 4% of US-based academics did their postdoc in the UK. The same academic can undertake a postdoc in more than one country, for example, 62 BBSRC researchers did a postdoc in the UK, and abroad. This is less common in the US sample where multiple postdocs tend to be in different universities in the US.

[17] For the UK sample a postdoc is defined as a postdoctoral positions or a research fellow appointment of less than five years. We considered research fellow positions of at least five years equivalent to lecturer, as they indicate a long-term relationship with the university, equivalent to a probation period (see also Fernandez-Zubieta et al., 2015). For the US postdoc is as assigned on the CV.

International and Career mobility

The second part of Table 3 presents a detailed set of statistics concerning job changes after the postdoc (job-job mobility). Based on CV information, we reconstruct the mobility paths of researchers from their career start (the year of their first job after PhD or after the postdoc for those with postdoc experience[18]) until 2012.

Table 3 Postdoc, International and Career Mobility

	UK		US		
	mean	Sd	mean	sd	Mean Diff
Postdoc	0.84	0.37	0.80	0.40	Ns
Postdoc in UK[1]	0.64	0.48	0.04	0.20	
Postdoc in US[1]	0.26	0.44	0.74	0.44	
Postdoc in others[1]	0.19	0.39	0.07	0.26	***
Job-job mobile	0.52	0.50	0.49	0.50	Ns
Times job-job mobile	0.78	0.95	0.78	1.02	Ns
International mobility (cross-border)	0.17	0.37	0.07	0.25	***
International mobility (EU as one)	0.13	0.34	0.07	0.25	***
International mobility (UK to US)[2]	0.02	0.14	0.02	0.13	
International mobility (US to UK)[2]	0.05	0.21	0.01	0.08	
Sector mobility (Industry - HEI/PRO)[3]	0.05	0.23	0.04	0.19	Ns
Sector mobility (PRO - HEI)[3]	0.10	0.30	0.05	0.21	***
HEI mobility (between HEI)[4]	0.40	0.49	0.42	0.49	Ns
Voluntary mobility (tenured HEI staff)[5]	0.35	0.48	0.24	0.43	***
Forced mobility (non-tenured HEI staff)[5]	0.07	0.25	0.26	0.44	***
HEI junior mobility (assistant or temp)	0.21	0.41	0.25	0.43	Ns
HEI senior mobility (associate or above)	0.25	0.43	0.26	0.44	Ns
UK HEI mobility	0.30	0.46			
UK HEI junior mobility	0.17	0.38			
UK HEI senior mobility	0.17	0.38			
EU HEI mobility	0.32	0.47			
EU HEI junior mobility	0.18	0.39			
EU HEI senior mobility	0.18	0.39			
US HEI mobility			0.40	0.49	**[6]
US HEI junior mobility			0.22	0.42	Ns[6]
US HEI senior mobility			0.25	0.43	**[6]
HE Career mobility (with promotion)	0.18	0.39	0.16	0.37	Ns
HE Career mobility - assistant to associate	0.09	0.29	0.09	0.28	Ns
HE Career mobility - associate to full	0.10	0.30	0.09	0.28	Ns
N	292		326		

*** p<0.01, ** p<0.05, * p<0.1

[1]The same academic can undertake more than one postdoc in two different countries. [2]Those moving from UK to US and those moving back overlap (the same person in both). [3]PRO in the UK sample includes mobility to UK Research Councils and European public institutions. [4]Includes cross-border mobility. [5]The same academic can be forced and voluntary mobile at different career stages. [6]Comparing the amount of within US mobility in NIH data to within UK mobility in BBSRC data.

[18] In the US sample about 95% of these are tenure-track or tenure-track equivalent positions. In the UK sample the first position is normally a lecturer appointment, but also research fellowships of more than five years and teaching contracts that are renewed on a rolling basis.

Most researchers are job-job mobile (51%) with no significant difference between the UK and the US; on average, researchers move between jobs 0.8 times in both countries. International job-job mobility (change of job that involves migrating to a different country) is much lower, dropping to 7% for the US sample and 17% for scientists working in the UK. When we exclude intra-European mobility for the UK sample, 13% of researchers still had international job experience during their career, indicating a higher internationalization for the UK sample compared to the US (connections with Commonwealth countries may play an important role here). International job-job mobility between the UK and the US (transatlantic mobility) is important (though it is small in absolute terms) especially for the UK sample with 5% of researchers having previously held a job in the US. Sector job-job mobility involving a move between industry and the public research sector (including higher education institutions (HEI) and public research organizations (PRO)) is small with about 5% of researchers having prior industry experience, in both samples. However, there is an important difference between the UK and US job markets with respect to sector job-job mobility between PRO and HEI, where 10% of UK researchers had a job in a PRO (including UK Research Council and European public research institutions), but only 5% in the US.

About 40% of researchers have changed higher education (HE) employer at least once (*HEI Mobility*) with no significant difference for the two samples. This similarity indicates that policy actions (such as the REF[19]) and incentives for mobility in the UK have made the UK system similar to the US with regard to academic mobility. For mobility within the higher education sector we can further distinguish between voluntary and forced mobility. The former is defined as a move after an academic is granted a permanent (tenured) academic post, while the latter is a move when occupying a fixed-term academic position. In the UK,

[19] See Moed (2008) for the changes in publications behavior (quantity and quality) encouraged by the Research Assessment Exercise (RAE), the precursor of the REF. See Elton (2000) for more general consequences of the RAE.

assistant professorships are considered permanent positions subject to a three-year probation period. In the US, assistant professorships are tenure-track positions and, thus, not permanent. If an academic moves before achieving associate professor status in the US, this is considered forced mobility. These differences in the academic markets result in significant differences in the number of forced and voluntary moves in the US and the UK samples. Amongst the BBSRC sample, 35% of academics move voluntarily to a different university, while only 7% are forced to move.[20] In the US, 24% change jobs while holding a permanent position, but 26% move while holding a fixed-term position. For comparison, we also look at junior (assistant and temporary jobs) and senior (associate and full professor) mobility and find that there is no significant difference between the two samples with about 25% of researchers in each group having experienced an academic job change.

Job-job mobility between universities in the same country is more likely amongst US-based academics (40%) than UK-based academics (30%). This is mainly due to the important role of intra-EU mobility (32%) and mobility between the UK and Commonwealth countries, which are especially important for associate and full professors explaining most of the difference between the UK and the US in *HEI senior mobility* (*HEI junior mobility* is not significantly different even at country level).[21]

Finally, for mobility associated with career promotion (promotion to a higher academic rank), there are no significant differences between the two samples. On average, job changes associated with promotion account for about 17% of cases.

[20] In the UK most contracts are permanent and forced mobility is usually observed before academics move to the UK or if they are on rolling teaching contracts.

[21] The difference persists if we control for similar career samples (e.g. only those that are full professors in 2012).

Career mobility by BA, PhD and Post-doc Location

In this section we analyze the career mobility figures in more detail by exploiting differences in location of education (BA and PhD) and postdoc. Table 4 splits the sample according to the location of the BA, PhD and postdoc and analyses the subsequent international mobility of the researcher.

Table 4 Career Mobility by BA/PhD/Postdoc Location

	UK		US	
	Mean	Count	Mean	Count
	BA Abroad			
Postdoc_Abroad	0.49	47	0.19	64
International job-job mobility (cross-border)	0.30	47	0.12	64
	BA Local			
Postdoc_Abroad	0.41	227	0.10	248
International job-job mobility (cross-border)	0.08	227	0.01	248
	PhD Abroad			
Postdoc_Abroad	0.54	46	0.29	35
International job-job mobility (cross-border)	0.22	46	0.20	35
	PhD Local			
Postdoc_Abroad	0.39	239	0.09	279
International job-job mobility (cross-border)	0.11	239	0.01	279
	Postdoc Abroad			
International job-job mobility (cross-border)	0.16	103	0.06	82
	Postdoc Local			
International job-job mobility (cross-border)	0.10	182	0.02	235

Researchers who studied for their BA or PhD outside their current location country are also more likely to have done their postdoc abroad. The correlation between foreign education and later postdoc or job abroad is higher for those located in the UK. For example, as shown in Table 4, 49% of those with a BA outside the UK also did a postdoc outside the UK compared to just 41% of those with a UK undergraduate degree. For the US these percentages are 19% versus 10%. The correlation between foreign education and subsequent international job-job mobility is even stronger. Scientists who studied abroad are more likely to be internationally mobile; those who obtained their undergraduate degree abroad are also more internationally mobile compared with those that did not (30% vs 8% in the UK and 12% vs 1% in the US). The PhD level results are similar, with 22% vs 11% for the UK and 20% vs 1% for the US. The UK sample shows a higher propensity to be internationally mobile respective to the US for both locally and internationally educated researchers. Considering the UK as part of the EU explains part of the international mobility in the UK sample, giving some evidence of a European job market for academics (mobility between continental Europe and the UK). However, even if we discount intra-European mobility we still see a higher level of internationalization for the UK sample compared to the US for BAs (abroad and local) and local PhDs.

Finally, if we look at postdoc location we observe similar trends; researchers that obtained a postdoc outside one of our two countries of interest are also more job mobile across countries later on, with those finally working in the UK being more internationally mobile compared to those finally working in the US. For higher education and postdoc location and mobility, we find some evidence supporting the view that being mobile during the training period affects the probability of being mobile during the remaining career. This shows a form of path dependence in which mobility in the education steps becomes a predictor of future international doctoral and job-job mobility. This is a possible avenue for future research.

5. Model and results

In the econometric analysis in this section, we focus our analysis on measuring the relationship between postdoctoral training and publication outcomes, controlling for the quality of the postdoc granting institution, education path and a variety of other individual and institutional factors. We address three main related research questions based on the unique availability of transatlantic mobility data. Our analysis is performed in three steps: First, we investigate whether academics that work in the US have a performance advantage compared to those working in the UK, and the role of postdoctoral training in this difference. Second, we investigate whether UK academics who did a postdoctoral fellowship in the US have a performance advantage compared to those undertaking a postdoc in the UK. Third, we investigate whether the US is able to retain the best postdocs by estimating the performance of academics in the US and UK that undertook a postdoc in the US. We limit the analysis to papers published from 1991 onwards since the number of researchers already active before 1991 is very small.

5.1 Dependent Variable - Publications

Journal publications were collected from the Medline database using PubHarvester (Azoulay et al. 2006).[22] The Medline database includes bibliographical information for articles published in the life sciences and biology. We collected publications for all the academics in our sample. Those with common name-surname combinations and those with Chinese last names were excluded and publications reliably collected for 512 academics, 244 UK academics and 268 US academics.

To account for journal impact/quality we matched each publication to the Journal Citation Report (JCR) published annually by Thomson Reuters. The JCR includes fewer journals than Medline and inclusion in that list can be considered a first impact/quality measure. The JCR also includes the Journal Impact Factor (JIF), which measures the average number of citations received by articles published in the focal journal in the previous three years, and can serve as a measure of impact/quality for articles published in that journal in the current

[22] See Annex 2 for a discussion of the disambiguation strategy followed.

year, although a controversial one (Bordons, Fernández, Gómez; 2002). As the JIF of a journal changes over time and journals are constantly added to (or removed from) the JCR, we matched publications to JCRs for each year from 1991 to 2012. For each publication we determine whether it was published in one of the top 5% of science journals (as defined by Thomson Reuters) in that year, thus creating a measure for the number of top impact/quality publications published by each academic in each year.[23] In addition we calculate the average JIF of all articles published by each academic in each year as a measure for the average impact/quality of their research.

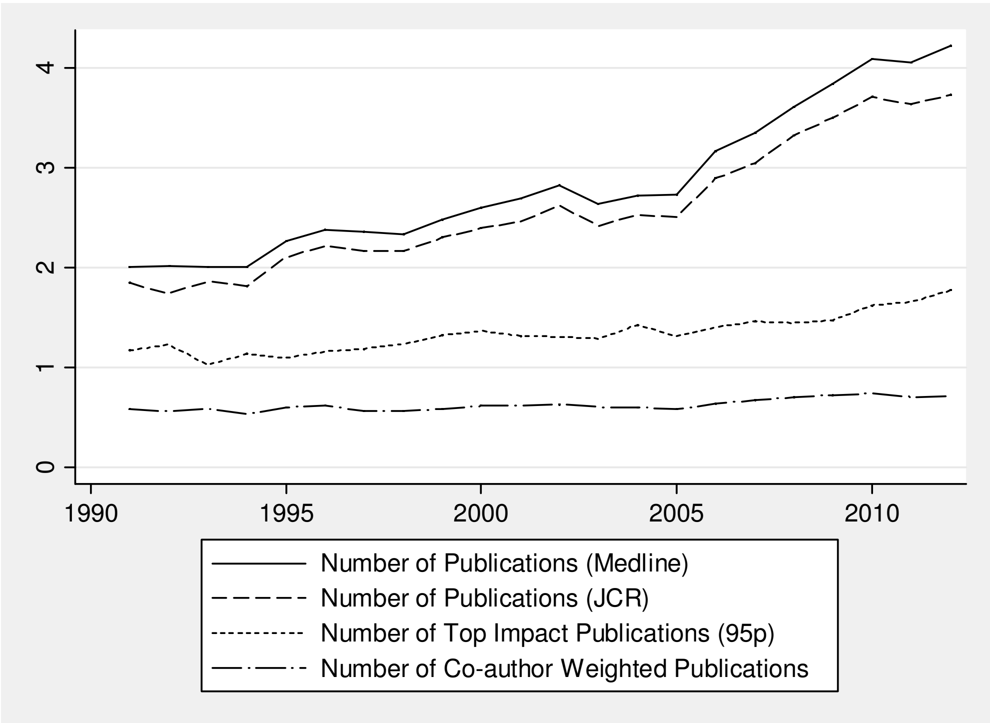
Figure 1 reports the average numbers of publications per academic per year as they appear in Medline, and also the number of publications that appear in JCR and the number of publications in the 95th percentile of journal impact/quality. Figure 1 shows that the average number of publications increased from 2.01 in 1991, to 4.22 in 2012. A similar increase is observed if we consider only publications that appear in JCR (from 1.85 to 3.73). The increase is less pronounced if we consider publications in one of the top science journals. The number is 1.18 in 1991 (representing 58% of publications) and 1.77 in 2012 (representing only 40% of publications).[24] Thus, while the number of publications has more than doubled over the past 20 years, the number of publications in top journals has increased by only 50%. In addition Figure 1 also reports the average number of publications per academic per year (Medline) weighted by co-authors. The number of co-authors per paper has increased significantly over the 20 year period from 2.54 authors per paper in 1991 to 7.09 authors in 2012, which may explains some of the observed increase in publication numbers. Figure 1 shows that the number of articles divided by the number of co-authors (the co-author

[23] The number of articles with an assigned JIF in our sample increased from 4,390 in 1991 to 8,423 in 2012. The average JIF in JCR increased from 1.085 to 2.053 over the same period. The highest JIF in 1991 was 37.16 and 153.459 in 2012. The JIF cut-off point for the 95th percentile was 3.281 in 1991 and 5.670 in 2012.

[24] The average JIF for publications in our dataset increased from 3.21 in 1991 to 4.69 in 2012, an increase of 50%.

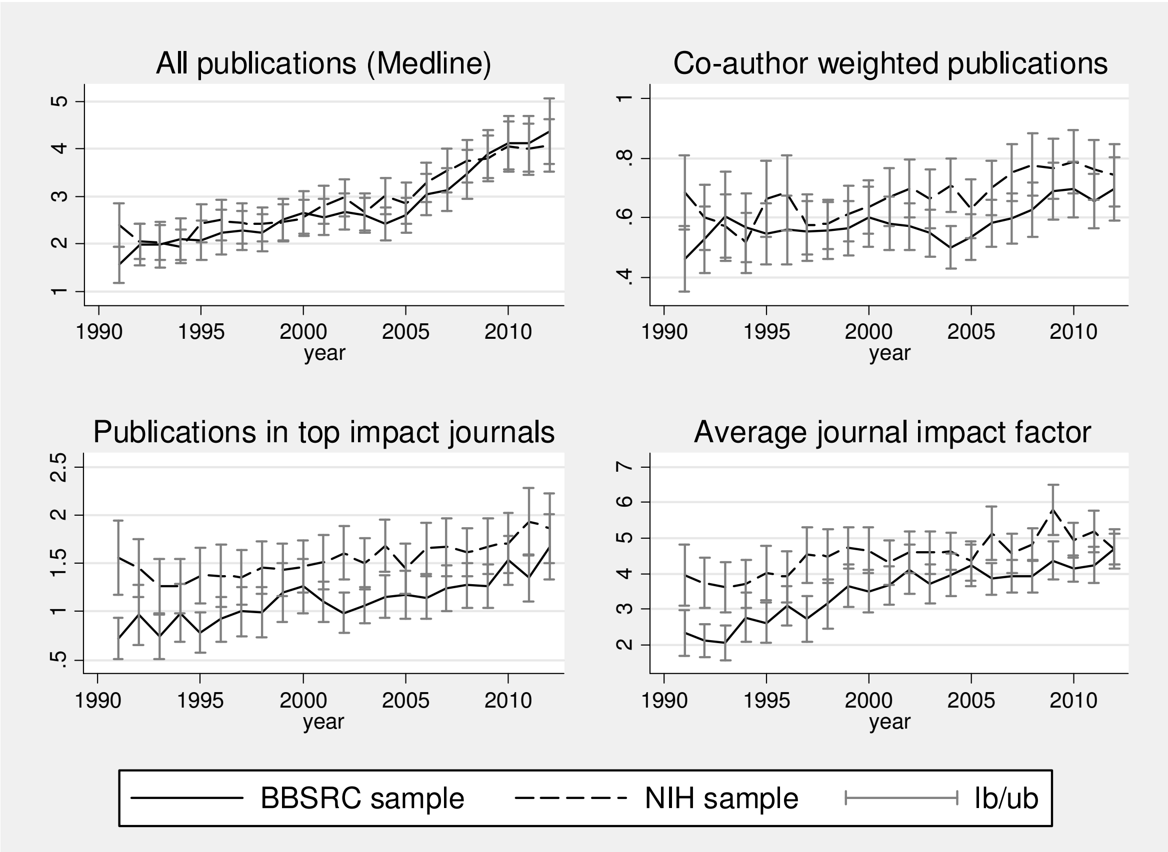
weighted article count) has increased at a much slower rate, from 0.58 in 1991 to 0.72 in 2012, an increase of just 25%.

Figure 1: Average Number of Publications per Academic per Year by impact/quality and by co-authors



Our data come from two different datasets: BBSRC and NIH. Figure 2 compares the performance of UK and US researchers and shows that the previously observed trend of an increase in publications can be found for researchers in both datasets. The average number of publications per year is slightly lower for researchers in the BBSRC sample, but the difference is not significant. However, academics in the UK publish fewer articles in the top 5% of journals, and articles of lower average impact/quality. This performance gap has been narrowing with no significant difference between the two samples since 1998. The graphs also show that academics in both the US and the UK have been able to increase the impact/quality of their research and the number of publications in top journals, however, most of this increase happened prior to 2000, with little to no significant increases since.

Figure 2: Number of Publications by Dataset



5.2 Identification strategy

The descriptive statistics suggest that academics in the US have a performance advantage compared to those in the UK. We therefore want to estimate this performance premium (the difference in publication performance between US and UK researchers) empirically. Since this potential premium may be related to the location of postdoctoral training, we include measures that compare the performance of academics that did their postdoc in the US to those that did their postdoc in the UK or some other country and to those with no postdoc, while controlling for education background and other personal and institutional characteristics.

This simple model does not account for the quality difference in postdoctoral training. Therefore, we include a control that allows us to compare the performance of researchers that did their postdoctoral training in a top biomedical training institution against those that did their postdoctoral training in a less important institution. This allows us to distinguish between the publication premium for a postdoc in the US compared to the UK, and the publication premium that is attributable to institution quality.

This first analysis combines various questions in a heterogeneous sample. As a second and third step we base our estimation on the difference-in-difference (DD) approach using a subpopulation of our sample. In the second model we limit our estimation to academics working in the UK who did a postdoc in the US or in the UK. We exclude academics that did their PhD in the US (but were working in the UK) so as not to confound the US postdoc effect with a US PhD effect. This approach is preferable to a regression that includes researchers of all career paths, which does not account for the unobserved heterogeneity of training background. Further, models that include both US and UK researchers do not allow us to check whether researchers with US training also perform better outside the US. Thus, based on the UK sample, we use a DD identification that allows us to compare the performance of researchers whose postdoctoral training was in the US compared to those that took up a postdoc in the UK. This enables us to investigate whether there is a US postdoc premium also for academics working in the UK academic market. Also, we consider that a US performance premium might be limited to receiving postdoctoral training at a top US institution. The DD is thus able to tell us whether the US postdoc premium is attributable to institution quality. As a third step we compare the performance of academics who work in the US with those on similar training paths who work in the UK. We limit the sample to academics who completed their postdoctoral training in the US to account for the unobserved heterogeneity of postdoctoral background. This DD identification also allows us to compare the performance of researchers that did their PhD training in the US with those that did their PhD training elsewhere. The DD thus distinguishes between the publication premium from working in the US (our main variable of interest) and the publication premium attributable to PhD training.

Postdoc quality measure

In order to assess the importance of a US postdoc for future performance, we need to identify those institutions that will provide the greatest prestige or performance benefit, or that are more likely to attract or select the most promising young researchers. We construct a ranking of US universities based on the US National Research Council's assessment of doctorate programs, which is undertaken approximately every 10 years. This assessment, available in a more or less comparable manner from 1982 onwards, evaluates the quality of US universities by subject area. We limit the ranking measure to doctoral programs in bioscience and biochemistry and identify those programs that were ranked amongst the top 10% in their field for the years 1982, 1993 and 2005. We then generate an indicator variable that takes the value 1 if a postdoc was undertaken in one of the top 10% of universities.[25] Postdocs undertaken before 1985 use the 1982 ranking, those before 1995, the 1993 ranking and those after 1995, the 2005 ranking. Eight universities are ranked in the 90th percentile in all three periods.[26]

We also rank UK universities using a disciplinary research ranking measure based on publication productivity and quality of the institution. We use Web of Science (WoS) publication data on UK universities compiled by Thomson Evidence, for the biomedical

[25] In the 1982 sample we identified 13 top universities. For 1995 and 2005 we identified 15 top universities due to the larger number of evaluated programs.

[26] See Table A1 in Annex 3 for a list of universities.

sciences for the years 1994 to 2009. We calculate the impact weighted productivity (IWP) of a given department per year (excluding those with an IWP of zero) and identify those in the top 10% as high quality institutions.[27] Nine institutions appear amongst the top 10% (14 institutions) for all the years. For those undertaking a postdoc prior to 1994, we use the 1994 ranking, and for those undertaking a postdoc after 2009, we use the 2009 ranking. Though this is not a perfect measure, it gives some indication of whether the postdoc was undertaken at a top quality department.[28]

Amongst the NIH academics undertaking a postdoc, 114 did a postdoc at one of the top US institutions (48% of those with a US postdoc) and 9 at one of the top UK institutions. Amongst the BBSRC academics, 25 (34% of those with a US postdoc) did a postdoc at a top US university and 119 at a top UK institution (65% of those with a UK postdoc). Eleven BBSRC academics undertook postdocs at a top US and a top UK institution (31% of those with US and UK postdoc).

Empirical Model

We estimate our baseline model and the DD models as Poisson regressions to account for the count nature of our data (numbers of publications).[29] This leads to an exponential functional form estimation equation for our baseline model:

$$\lambda_{it} = E[P_{it}|USJob_i, PD_i, X_{it}] = \exp(\propto USJob_i + \beta PD_i + X'_{it}\gamma)$$

[27] See Lawson and Soos (2014) for a detailed explanation of the ranking indicator, and Fernández-Zubieta, et al. (2015) for an application to a sample of UK scientists in natural and engineering sciences.
[28] Results are robust if we only consider academics that finished their PhD after 1990, i.e. did their postdoc in the last 20 years for which rankings are available.
[29] The average journal impact factor is a non-integer value but it follows a Poisson process and is consistent if robust standard errors are specified.

where P_{it} is the count variable which represents the publications by academic i in t and is assumed to be Poisson distributed with $\lambda_{it} > 0$. $USJob_i$ is the measure for a job appointment in the US (NIH dataset), $Postdoc_i$ denotes the postdoc experience of the academic and X_{it} the set of controls for age, gender, PhD country, and institution type, as well as year and career start year (the year of their first job after PhD or after the postdoc for those with postdoc experience) fixed effects.[30] The Poisson model assumes equidispersion which is often violated in models of publication counts, leading academics to prefer the negative binomial (negbin) model. However, the negbin model is only consistent if the variance term is correctly specified while Poisson models are consistent with only the mean correctly specified, even if overdispersion is present. The standard errors in the Poisson model can be corrected by applying robust standard errors (Wooldridge, 2002).[31] Standard errors are further clustered at the level of the individual, allowing estimation of a random effects Poisson model.

The number of academics is reduced to 498 due to missing values in some of the explanatory variables; the reduced sample is still comparable between the US and the UK with regard to gender and education mobility of academics; BA and PhD graduation year are different (as in the total sample), but the same within a three year cohort. There are more full professors in the US compared to the UK sample. In the UK sample we also have a group of young scientists who were not awarded a grant as PI before 2012 (only Co-I grants). We include a control in the regressions to capture any potentially missing experience effect of these Co-Is

[30] Results are robust if we include additional controls, e.g. past job mobility, current country of employment or seniority. These measures raise endogeneity concern, however, and are therefore not included in the models presented here.

[31] The consistency of the negbin model is further rejected in the publication impact/quality models. It would be appropriate for the publication count model, which is more skewed, to use negbin, but the results are very similar and since the Poisson estimates are more conservative they are preferred.

(see Table A1 in Annex 4 for descriptive statistics for all the variables included in the regression).

5.3 Results

The main results are presented in Table 5 and are shown for three different performance measures: 1) the total number of publications, 2) the number of publications in top journals, and 3) the average journal impact factor of all publications. We report the marginal effects. The results we find for the total number of publications (measure 1) are confirmed if we consider only the number of publications in JCR journals or if we weight the number of publications by the number of co-authors.[32]

The results show that generally women produce significantly fewer publications than men and fewer in top journals, but that their publications are of equal average impact/quality. The number of publications and their impact/quality increase with age, albeit with diminishing returns.[33] Researchers publish fewer articles, but not articles of lower impact/quality, when employed at private sector firms compared to employment at universities. Those working at research hospitals publish fewer articles in top journals, and of lower average impact/quality, than those working in a university department. Performance does not change when researchers work for public research organizations. We included year and career start year fixed effects, they are jointly significant. The results are also confirmed if we include an

[32] Results are available from the authors upon request.

[33] As the US and UK promotion systems are different, due to endogeneity concern we do not include a seniority control in our models. However, in robustness checks that include seniority measures we would find that the number of publications and their impact/quality increases with seniority and is highest for full professors. The age effect for impact/quality would become insignificant.

experience (defined as number of years since career start) or a PhD year (year of PhD award) fixed effect in place of the career start year fixed effect.[34]

The US sample dummy is positive and significant in all estimations, showing that, all else being equal, academics working in the US on average produce 1 publication and 0.9 publications of high impact/quality more than those in the UK, while the average impact/quality of their publications is 1.76 points higher than that of UK based academics

The postdoc dummies show that academics that undertook a postdoc do not produce more publications than those without a postdoc and also do not publish more in top impact journals.[35] However, academics with postdoctoral experience publish in journals of higher average impact/quality than those without. The differences between the countries in which the postdoc was held are not significant, meaning that those with a postdoc in the US do not publish more than those with a postdoc in the UK once we control for country of employment and other factors.

The quality dummy for the postdoc institution (Top US/Top UK) further allows us to see if those coming from top institutions publish more compared to those from other institutions or those without a postdoc. We find that those with a postdoc in a top UK or US university do not publish more articles than other researchers. Also, despite the large positive coefficient, top UK postdocs do not publish significantly more articles than top US postdocs (test of equality between UK and US top postdoc is only rejected at the 11% significance level). We find, however, that top UK postdocs publish more articles in top impact journals compared to

[34] Results are available from the authors upon request.
[35] Note that our results might underestimate the contribution of foreign PhDs and postdocs as we excluded Chinese names from our sample for technical reasons (see Annex 2).

those without a postdoc or a postdoc in a country other than the UK or the US, but do not have a significantly higher average impact factor. For the top US postdoc, we find no significant added performance premium in terms of number of publications in either all or top impact journals. The top US postdoc, however, is associated with a higher average JIF of 0.6. This positive correlation remains if we exclude academics without postdoc experience, showing that top US postdocs produce research of higher average impact/quality than those with a postdoc elsewhere.

We also control in our estimations for PhD education and find a negative marginal effect of a US PhD on publication numbers and top publications, but not significant on average impact/quality. Most academics with a US PhD remain in the US and, thus, continue to produce more publications than researchers working in the UK. But, they produce fewer publications and fewer top publications than academics trained outside the US that moved to the US for a job or for a postdoc and stayed there to further their careers.

Table 5: Postdoc and Job Effect on Performance - Poisson estimation on full sample

	Publication number (Medline)				Publication number in top journals (95p)				Average journal impact factor			
female	-0.593**	(0.255)	-0.564**	(0.255)	-0.286**	(0.142)	-0.286**	(0.145)	-0.098	(0.287)	-0.156	(0.288)
age	0.400***	(0.065)	0.397***	(0.063)	0.197***	(0.036)	0.198***	(0.036)	0.200***	(0.071)	0.228***	(0.069)
age^2	-0.004***	(0.001)	-0.004***	(0.001)	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.001)	-0.003***	(0.001)
US Job	1.018**	(0.436)	1.111***	(0.422)	0.908***	(0.231)	0.910***	(0.219)	1.761***	(0.527)	1.646***	(0.514)
US Postdoc	-0.041	(0.246)			0.130	(0.139)			0.713***	(0.267)		
UK Postdoc	0.225	(0.312)			0.183	(0.185)			0.764**	(0.332)		
Other Postdoc	-0.196	(0.327)			-0.029	(0.162)			0.606**	(0.306)		
Top US Postdoc			-0.101	(0.259)			0.221	(0.147)			0.603**	(0.260)
Top UK Postdoc			0.471	(0.289)			0.302*	(0.177)			0.482	(0.301)
US PhD	-0.843*	(0.483)	-0.763*	(0.458)	-0.358*	(0.195)	-0.335*	(0.186)	-0.458	(0.461)	-0.592	(0.467)
UK PhD	0.072	(0.470)	0.161	(0.448)	0.184	(0.212)	0.196	(0.204)	0.303	(0.500)	0.246	(0.501)
University	Reference											
Firm	-1.072*	(0.627)	-1.177*	(0.620)	-0.092	(0.286)	-0.140	(0.284)	0.721	(0.578)	0.733	(0.648)
Research Hospital	-0.937	(0.790)	-0.998	(0.801)	-1.360***	(0.483)	-1.265***	(0.473)	-2.508**	(1.060)	-2.187**	(1.006)
PRO	-0.450	(0.468)	-0.399	(0.483)	-0.446	(0.379)	-0.370	(0.376)	-0.306	(0.756)	-0.151	(0.722)
Co-I Control	0.201	(0.485)	0.265	(0.486)	0.200	(0.242)	0.225	(0.250)	0.003	(0.511)	0.009	(0.546)
N	8768		8768		8768		8768		8768		8768	
N_clust	495.000		495.000		495.000		495.000		495.000		495.000	
log-likelihood	-22543.809		-22515.894		-15390.117		-15352.190		-28352.604		-28403.475	

Marginal Effects are reported; Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01;
All estimations include year and career start year fixed effects.

Table 6: DD Poisson - Postdoc Effect for BBSRC Researchers

	Publication number (Medline)				Publication number in top journals (95p)				Average journal impact factor			
female	-0.279	(0.530)	-0.195	(0.540)	-0.061	(0.244)	-0.032	(0.258)	0.260	(0.475)	0.199	(0.498)
age	0.526***	(0.137)	0.520***	(0.138)	0.284***	(0.068)	0.284***	(0.069)	0.187	(0.128)	0.188	(0.126)
age^2	-0.004***	(0.001)	-0.004***	(0.001)	-0.003***	(0.001)	-0.003***	(0.001)	-0.002	(0.001)	-0.002*	(0.001)
US Postdoc	-0.136	(0.454)			-0.009	(0.252)			0.613*	(0.324)		
Top US Postdoc			-0.847	(0.715)			-0.065	(0.377)			1.253***	(0.444)
Top UK Postdoc			0.453	(0.378)			0.226	(0.203)			0.087	(0.354)
University	Reference											
Firm	-1.976***	(0.742)	-2.221***	(0.750)	-0.172	(0.297)	-0.297	(0.294)	0.607	(1.523)	1.694	(1.694)
PRO	-0.136	(0.577)	-0.451	(0.627)	-0.125	(0.359)	-0.086	(0.387)	-0.519	(0.964)	-0.428	(0.973)
Co-I Control	-0.563	(0.602)	-0.451	(0.585)	-0.054	(0.261)	-0.017	(0.259)	0.019	(0.540)	0.131	(0.588)
N	3041		3041		3041		3041		3041		3041	
N_clust	178		178		178		178		178		178	
log-likelihood	-7714.395		-7675.299		-4964.614		-4952.198		-8974.079		-8951.882	

Marginal Effects are reported; Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01;
All estimations include year and career start year fixed effects. There are no research hospital observations.

Table 7: DD Poisson - US Job Effect for US Postdocs

	Publication number (Medline)				Publication number in top journals (95p)				Average journal impact factor			
female	-1.134***	(0.372)	-1.133***	(0.372)	-0.462*	(0.252)	-0.458*	(0.251)	-0.136	(0.461)	-0.118	(0.460)
age	0.391***	(0.089)	0.392***	(0.089)	0.212***	(0.052)	0.216***	(0.053)	0.199*	(0.109)	0.205*	(0.110)
age^2	-0.005***	(0.001)	-0.005***	(0.001)	-0.003***	(0.001)	-0.003***	(0.001)	-0.003***	(0.001)	-0.003***	(0.001)
US Job	1.171**	(0.573)	1.153*	(0.589)	0.989***	(0.311)	0.884***	(0.295)	1.771***	(0.623)	1.619***	(0.622)
US PhD	-0.226	(1.029)	-0.227	(1.030)	-0.280	(0.515)	-0.305	(0.488)	0.548	(0.855)	0.517	(0.815)
US PhD*US Job	-1.014	(1.131)	-1.008	(1.136)	-0.398	(0.564)	-0.350	(0.531)	-1.875*	(1.021)	-1.793*	(0.979)
Top US Postdoc			0.055	(0.281)			0.311*	(0.172)			0.517	(0.316)
University	Reference											
Firm	-0.861*	(0.460)	-0.857*	(0.462)	0.145	(0.339)	0.184	(0.326)	1.588	(1.555)	1.637	(1.603)
Research Hospital	-1.387*	(0.840)	-1.364	(0.844)	-1.532***	(0.507)	-1.376***	(0.503)	-1.962	(1.564)	-1.722	(1.510)
PRO	-0.511	(1.133)	-0.499	(1.136)	-0.322	(0.605)	-0.243	(0.617)	-0.432	(1.305)	-0.254	(1.299)
Co-I Control	0.765	(0.688)	0.761	(0.689)	0.679*	(0.369)	0.666*	(0.370)	0.815	(0.778)	0.813	(0.794)
N	4374		4374		4374		4374		4374		4374	
N_clust	253		253		253		253		253		253	
log-likelihood	-10708.791		-10708.381		-7640.136		-7614.343		-14669.239		-14645.079	

Marginal Effects are reported; Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01; All estimations include year and career start year fixed effects.

DD Estimation 1 – UK sample

The baseline model in Table 5 shows that academic performance is higher in the US. It also indicates that those that took up a postdoc in a top US institution perform better in terms of impact/quality than those undertaking a postdoc elsewhere, even when working in the UK. A top UK postdoc is associated with a higher number of top impact/quality publications compared to those without a postdoc, but not with higher average impact/quality. To confirm the robustness of this result, in a second step we analyze whether UK based academics that undertook a postdoc in the US perform better compared to UK based academics that did a postdoc in the UK. We limit the analysis to academics whose PhD degree was awarded outside the US in order to measure only the additional performance premium of a US postdoc and not confound it with a potential US PhD correlation. The results are presented in Table 6.

The results show no significant differences between men and women for any of the performance measures. Publication numbers, but not average impact/quality of the publications, increase with age. We also checked the results including seniority variables, and the results are robust, with age turning insignificant.[36]

For the postdoc measures, we find that academics in the UK with a postdoc at a US institution do not publish more articles than those with a UK postdoc. However, in the model that predicts the average JIF, we find a strong positive result for academics that did a postdoc at a US institution, increasing the average journal impact/quality by 0.6 points. We also compare the performance of those that did their postdoc at a top US or top UK institution, to the performance of academics with a postdoc at a lower quality institution. The results confirm that top UK postdocs do not have a significantly different effect on publication

[36] Estimations including seniority might potentially suffer from endogeneity. Results including seniority measures are available on request

numbers or impact/quality than those at lower quality institutions. At the same time, we find that academics with a US postdoc publish fewer articles, but that these are of higher average impact/quality. The average JIF of their publications is 1.3 points higher than that of all other academics. Thus, even in a market outside the US those with a postdoc from a prestigious US university produce research of higher average impact/quality. However, they do not produce more top articles or more publications in general.

DD Estimation 2 – US Postdoc sample

In the base model in Table 5 we found a performance premium for scientists working in the US, and in the second estimation in Table 6 we found a performance premium for UK researchers with a postdoc in the US. We are further interested in whether the US is able to keep the most talented researchers in the biomedical sciences. As a next step, we therefore reduce the analysis to academics with a postdoc in the US and check whether those staying in the US perform better than those that move to the UK. Table 7 reports the results of the estimation.

We see that women with a US postdoc produce fewer publications and fewer publications in top journals than men with a US postdoc, but the average quality of the publications is equal for men and women. Age has a positive significant effect, with diminishing returns.

Our results show that those US postdocs that continue to work in the US publish more and of higher impact/quality compared to those that move to the UK. However, those that also completed their PhD education in the US publish articles in journals of lower average impact/quality than those that moved to the US from abroad to do their postdoc. We also checked the robustness of these results by dropping the PhD-job interaction variable and the results do not change. The main US Job effect remains strong and positive, although with a slightly smaller marginal effect, and the US PhD effect is negative and significant in all estimations. The second set of models in Table 7 includes a control for whether the US postdoc was completed in a top US institution. While the postdoc quality measure is not related to publication numbers, it is positively correlated with the number of articles in top quality/impact journals and average journal impact/quality (at 11% significance). These results confirm that PhD education in the US is not correlated to achieving higher publication performance; also, the combination of a PhD, postdoc and job in the US tends to result in lower impact/quality adjusted performance compared to academics working in the US with a more international career path. To summarize, we find some evidence that the US system is able to retain high performing academics who completed their PhD degree in another country and went to the US to do their postdoc (especially at top US departments).

6. **Conclusion**

Biomedical science is an important and growing area of academic research, led by the US and the UK, which are able to attract promising researchers from other countries. The field is characterized by a highly internationalized labor force and increasing collaboration between researchers (NIH, 2012; BIS, 2013). This is an ideal setting to study academic labor market characteristics, mobility patterns and the correlation between international (specifically transatlantic) mobility and research performance across career stages (student, postdoc, untenured, and tenured job levels). In order to carry out this analysis, we constructed the BIOMEDMOB database that includes original individual level data extracted from CVs and semi-automated information on academic performance. This allowed us to trace researcher's movements along their careers, across countries and jobs, while tracking also their academic performance. These unique dataset made it possible to compare the two labor markets in their ability to attract researches at all career stages and to identify the performance premium associated with these different career stages.

The analysis presented in this chapter was based on a sample of 619 US and UK biomedical researchers (327 from the US and 292 from the UK) in the period 1956 to 2012. We found that postdoctoral stays are common among biomedical academics (81%) and that most are located in the US or the UK, although about 20% of researchers working in the UK and about 25% working in the US had undertaken a post-doc in a third country. We found that job changes following the postdoc are common, with about 50% of our sample having changed jobs at least once since their first appointment after the postdoc. We did not find a higher mobility rate for the US sample. In relation to mobility within academia, mobility between universities within the domestic labor market is smaller in the UK than in the US. However, if we take into account international mobility (for example EU and Commonwealth mobility), we find a mobility rate similar to that in the US. Also, in terms of mobility for promotion and mobility to and from industry we found no significant differences between the two samples. Incentives and policy action implemented in the UK during the last 20 years seem to have resulted in a UK academic market for biomedical sciences that is similar to the US market with regards to academic mobility.

We observed that publication patterns have changed considerably over the two decades under study, with output increasing more in quantity than impact/quality and a narrowing of the impact/quality gap between the UK and the US. The number of publications has more than doubled over the period 1991 to 2012, while the number of publications in top journals has increased at a much slower pace (a 50% increase). The number of co-authors per paper has nearly tripled over the 20 year period; if we consider the number of articles per co-author then total publication numbers increased by only 25%. Comparing the research performance of academics in both countries, we found that UK based academics publish less frequently in higher quality journals (top 5% journals) and have a lower average journal impact factor, although they had been able to reduce this impact/quality gap with US based academics.

This initial evidence led us to investigate further the degree and source (in terms of career stage) of this performance premium for researchers working in the US. First, we analyzed the effect of US postdoctoral training (compared to a similar training in the UK, in other countries or no postdoctoral training) and its quality, controlling for education background and other personal and institutional characteristics. We confirmed the performance premium for US-based academics in terms of number of publications, publications in top journals and average journal impact factor. The results for the whole sample (researchers working in both the US and the UK) show that academics with a US or UK postdoc do not publish more than those without this training, but they appear to publish in journals of higher average impact/quality. Postdoctoral training seems more relevant when conducted at a top-quality institution. We found some evidence of a positive correlation between doing postdoctoral training in a top-quality UK institution and publications in top journals and a significant correlation between having top postdoctoral training in the US and subsequent average publication impact/qualityJIF. These results are consistent with Long (1978) who found that postdoctoral training is especially important for publication quality. The weak negative results (for total publications and publications in top journals) of PhD training in the US supports the US's ability to attract the best researchers worldwide at postdoctoral level, and give them a research advantage.

We also examined whether this 'US postdoctoral training' advantage is transferable geographically and holds for researchers working in the UK. We reduced the heterogeneity of our sample by focusing only on UK based academics who received their PhD training outside the US, to measure the US postdoctoral effect and perform estimations, by employing a DD style approach. The results confirmed that US postdoc training is associated with publications of significantly higher average impact/quality later in the academic career in the UK (although lower publication numbers). This premium is higher if the postdoctoral training is undertaken in a top US institution.

We also investigated whether the US was able both to attract the best researchers and give them performance advantages, and to retain the best researchers. We applied the same DD style approach but focused on academics with a US postdoc to check whether those who stayed in the US perform better than those that leave. The results show that researchers with a US postdoc who stayed in the US gain a performance premium. However, those who did their PhD in the US publish articles of lower average impact/quality than those that move to the US for a postdoc.

Among the control factors, we found a positive correlation between academic rank and our various measures of research output, which is stronger for the US than the UK sample. We also found evidence for the US sample that female researchers show lower productivity in terms of total publications and publications in top journals, but are similar to men with regard to the average impact/quality of publications. For the UK we found no differences for any of these measures.

Overall, our results provide some support for the view that postdoctoral training is a crucial mechanism for attracting top researchers to the US, that this offers researchers a performance premium in terms of research quality, and that this premium is stronger if the training takes place in a top institution. The performance premium found for researchers that undertook postdoctoral training could be attributable to the selection procedures applied in the US, the resources available, or other institutional and social advantages. We did not have the necessary information and sufficient number of observations to properly test the selection hypothesis. Also, we did not consider the duration of post-doctoral training. This might allow better qualification of our positive results for postdoctoral training in the future, as we would expect a decrease in performance for longer postdoc periods. However, we also cannot say anything about the negative consequences of increasing the duration of postdoctoral training or repeated temporary contracts that also increase in both countries, issues that are heavily discussed in the policy literature.

Finally, the higher performance of US researchers could be attributable to the US university system's ability to attract, select and retain the best researchers worldwide and to give them the resources and institutional and social advantages to improve their performance. In the set up in this chapter we could not test these reasons. However, it is interesting to note that the UK academic system in biomedicine is highly internationalized (and even more so than the US in relation to late career mobility), it shows as much mobility and competitiveness as the US, and it has a promotion path associated with mobility that is similar to the US. Thus, it seems that the UK and US academic labor markets are very similar. Researchers working in the UK of similar age and education to researchers working in the US, still underperform compared to their US counterparts. Resources, institutional and social advantages might be reasons for this difference.

In a research world with increasing level of mobility across countries and career stages and countries competing for global talent, this chapter makes it possible to learn more about the individual consequences of internationally mobile researchers, which might help countries to fine-tune their policies, institutions to manage mobile researchers, and researchers to improve their career choices. For example, if our results were to be confirmed, postdoctoral mobility (to top institutions) seems to offer better returns to the individual scientist, the receiving system, and the sending system (if the scientist returns) compared to PhD mobility. Public support (or individual decision) for postdoctoral mobility (or for attracting foreign postdocs) seems to be more justified than support for PhD mobility. The higher level of information at the postdoctoral level allows a better match between foreign researchers and hosting institutions, facilitating the rootedness of foreign researchers in local social networks and culture (as our results on average impact/quality suggest for the US sample) that appears to have a future impact on performance in both the case of a return to the sending country or the case of staying in the hosting country.

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Annex 1: Data Construction and Response Analysis[37]

US Sample

For the US we use research project grants (R01) awarded by the National Institute of Health (NIH), the leading funding agency for academic research in biomedicine in the US. NIH grant award data cover grants awarded by the NIH since 1970 and include personal identifiers (ids) for principal investigators (PIs) since 1985. They also provide information on university and subject affiliation for all funded researchers. R01 grants are assigned to around 230,000 PIs which include university researchers as well as researchers from NIH institutes and industry. We limited our sample to researchers that received at least one R01 grant during the period 2001 to 2010 and were working for a university at the time of grant award. We further limited the sample to academics that worked in departments of biology, chemistry, neurology, genetics or their sub-fields (at schools of medicine, arts and science, graduate colleges or schools of engineering) at the time of grant award. This left us with an initial sample of 10,221 PI identifiers.

To collect CVs, we utilized the SiSOB tool (Geuna et al. 2015).[38] First, we crawled the personal web pages of researchers and identified 4,037 valid email addresses (representing 40% of the original sample). All researchers were surveyed to collect CV and personal information. The survey was conducted in five rounds from October 2013 up to April 2014 and resulted in 169 valid CVs (a response rate of 4%). Second, we crawled the web for researchers' CVs, a process that resulted in 215 correctly identified CVs. The final set of US CVs consists of 384 entries representing 3.8% of the initial population of 10,221 academics.

To test for non-response bias we firstly rely on university affiliation as an indicator involving a number of dimensions such as geographic distribution, size and institutional quality of the two groups. The analysis of institutional distribution revealed a total of 309 universities in the full population and 135 in the respondents' sample (42%) which account for 80% of the most important institutions in the full population. In order to formally address the representativeness of the sample we used the Wilcoxon Rank Test. As a result, we found a significant match between the two distributions (population and respondents) with a 5% degree of tolerance, suggesting that the sample is not significantly different from the total population. To address additional concerns over sample bias at the individual level we compare the distribution of subject areas, number of years actively involved in NIH sponsored research and number of grants in the full population and the sample population. We perform Kolmogorov–Smirnov tests of the equality of distributions and find that there is no significant difference between the years of grant activity in the respondent sample and those that did not answer (15.93 vs. 16.01 years since first grant, $\rho = 0.539$). However, we find some difference in the number of grants (2.7 vs. 2.8 grants, $\rho = 0.003$) and in the field distribution ($\rho = 0.035$). As a robustness check, we test the hypothesis excluding the field of chemistry, which has the highest response rates, and no longer find significant field differences ($\rho = 0.177$). Among our respondents 76% are life scientists and 24% are chemists (compared to only 10% chemists in the original population).

UK Sample

[37] The data description and response analysis was also published in Section 5 of Geuna et al. (2015).

[38] The SISOB Tool is an open source web application used to search, identify and codify information on the careers of academic scientists identified on the web. The tool consists of five main items: 1- Crawler, 2-Email Extractor, 3-CV and Web Page Extractor, 4-Email Survey, and 5-Text Analyzer and Codifier.

For the UK, we use grants awarded by the Biotechnology and Biological Sciences Research Council (BBSRC), the leading funding agency for academic research and training in non-medical bioscience in the UK, from 1994 to 2010, and include personal identifiers for 7,527 researchers. The database includes both PIs and Co-investigators (Co-I). We limit the sample to those researchers that received at least two grants during the period 1994 and 2010, resulting in a list of 3,615 researcher IDs, which include academics but also researchers working in industry and public research laboratories. In order to gather more thorough and up-to-date information (the most recent grant received by some researchers was in the 1990s) and to identify academics, we cross-referenced these researchers with the 2008 Research Assessment Exercise (RAE). RAE 2008 includes a comprehensive listing of all research-active staff in all UK universities, for 2007. Amongst the 3,615 researchers that received at least two BBSRC grants since 1994, we identified 2,426 submitted to RAE 2008 by their university departments. Thus, they could be identified as working at a UK university in 2007. To collect CVs for the BBSRC sample, we firstly collected email addresses manually and gathered valid email address for all 2,426 researchers. All researchers were surveyed to ask for their CVs and additional personal information (family situation, nationality). The BBSRC survey consisted of nine rounds, from September 2011 to January 2014, resulting in 296 (12.2%) complete CVs. The, using the SiSOB tool (Geuna et al., 2015) we directly crawled the web for researchers' CVs. This process resulted in 13 additional correctly identified CVs. The final UK database then consists of 309 CVs, corresponding to a response rate of 12.7% from the initial set of 2,426 academics.

To test for non-response bias we used the institutional composition of the full population and the sample of respondents based on RAE and BBSRC information. Academics in the full sample population come from 81 universities and respondents from 52 (64%) which account for 80% of the top institutions. Again we find no difference in population based on universities represented (Wilcoxon Rank Test). We also compare the distribution of the amount of funding received, grant numbers, years actively involved in BBSRC sponsored research, and subject areas by the full and the sample populations (using Kolmogorov–Smirnov tests). We find no significant difference in grant value (£1.82 million vs. £1.78 million, $\rho = 0.352$) or in grant numbers (5.2 vs. 5.1, $\rho = 0.491$) between the respondent sample and those that did not answer. There is a small difference in years since first grant (12.7 vs. 13.3, $\rho = 0.040$) with the respondents sample being slightly younger than non-respondents. We find no differences in the subject area distribution ($\rho = 0.763$).

Annex 2: Disambiguation Strategies for Publications

We searched for individual publications information for the full sample of 619 researchers using the open-source software Publication Harvester, which collects data from the open portal PubMed, a publication search engine for the Medline database. We applied a multi-search method to attribute publication records (articles) to individual researchers, addressing the "author name disambiguation" problem. This mechanism allows us to semi-automate the search and cleaning of publication records for each researcher, the equivalent manual process is time-consuming and requires other sources of information (e.g. full publication records to improve the cleaning process).

The author name disambiguation problem arises in two ways: an individual researcher may be identified as two or more authors (splitting) and/or several researchers may be identified as a single author (merging) (Milojevic, 1013). Frequently, author names are reported inconsistently across publications and some names are "shared" by different authors.

There are several automated methods for dealing with the disambiguation problem ranging from simple (Newman, 2001) to more advanced methods (Ferreira et al., 2012; Tang et al., 2012; Smalheiser and Torvik, 2009). Simple methods are name-based and use only author's name and initials, advanced methods require additional information (e.g. co-author names, article titles, subjects, affiliations, citation counts). However, advanced methods also need conceptual and computational efforts that do not necessarily improve accuracy (Moody, 2004; Milojevic, 2013) compared to the simple methods.

We applied a multi-method that involves name-based searchers, uses additional related information (e.g. PhD year) to establish the time-span of our search and considers the name frequency and the size of the dataset to improve accuracy.

We extracted all the publications using an all initials approach and including PhD year information. This method offers a restrictive framework to avoid merging-ambiguity (same last name that does not belong to the same author). We limited the year of publication based on the year of PhD award, imposing a three years window before, and 2013 for closing this window. The all initials method might introduce some inconsistencies in author identification (splitting-ambiguity). The same researcher can appear as Smith J. and as Smith J.C. depending on how the name was reported in the paper. Availability of a researcher ID would avoid this issue, but ID's are not implemented completely in PubMed. Although we might lose some publications from the same author (false negatives), we were more concern about avoiding the merging-ambiguity problem (false positives).

We determined the frequency of the names in our sample in order to identify further merging-ambiguity problems and clean the publication database. We were able to compute root frequencies (names plus first initial, name plus two initials, etc.) by manually downloading the publications from PubMed for the period 1965 to 2010. The final number of roots appearing at least two times is around 145,000.[39] Publication were reliably collected for 512 researchers after excluding very common roots (higher than five for names with one initial and higher than 19 for names with two initials) and Chinese names for which the disambiguation process did not work. Note that the all initials methods described above can

[39] We could not retrieve the whole set of publications from 1965 up to 2013 because PubMed does not allow this. Since the propensity to publish is quite high in medical sciences with respect to others we are confident that the 145,000 set of roots is highly representative of the whole set of authors listed in PubMed

be contaminated if the authors have not correctly reported their full name in their CV. In line with other name-based methods the hybrid method cannot disambiguate names with the same first and middle initials which may apply to several individuals, and more often affect Asian names (Milojevic, 2013).

The multi-method applied is the result of testing all the name-based approaches (first initial, all initial and hybrid method (Milojevic, 2013)) and more advanced methods in our database (PubMed). For example, we found that the use of quotation marks, a typical feature of PubMed in order to restrict the publication search, did not work properly with the Publication Harvester software. Once we implemented the script for the automatic search, Publication Harvester treated the Smith J [au] as if it were "Smith J" [au]. This resulted in *closing* instead of *opening* the search. Therefore we used the *all-initial* method, include CV information to restrict the search and use the frequency of the roots from the hybrid method to clean the publication outputs.

Annex 3: Top ranked institutions

Table A1: Universities that remain in the top 10 percent over the full sample period

US	
	California Institute of Technology
	Harvard University
	Massachusetts Institute of Technology
	Rockefeller University
	Stanford University
	University of California Berkeley
	University of California San Francisco
	Yale University
UK	
	University of Bristol
	University of Cambridge
	Imperial College London
	King's College London
	University College London
	University of Oxford
	University of Edinburgh
	University of Glasgow
	University of Manchester

Annex 4: Descriptive statistics

Table A2: Summary Statistics for Regression Variables

	All id=494				BBSRC id=238		NIH id=256	
	mean	sd	min	max	mean	Sd	mean	sd
Publication number (Medline)	2.94	3.36	0.00	41.00	2.88	3.39	2.99	3.33
Publications in top journal	1.36	2.00	0.00	22.00	1.15	1.75	1.54	2.18
Average JIF	4.14	4.39	0.00	51.30	3.65	3.97	4.57	4.68
Co-author weighted publication number	0.64	0.72	0.00	7.52	0.59	0.67	0.68	0.76
Publication number (JCR)	2.68	3.12	0.00	37.00	2.62	3.13	2.75	3.12
Female	0.21	0.41	0.00	1.00	0.22	0.41	0.21	0.40
Age	46.54	10.00	26.00	89.00	44.67	8.70	48.19	10.76
US Postdoc	0.50	0.50	0.00	1.00	0.25	0.44	0.72	0.45
UK Postdoc	0.32	0.47	0.00	1.00	0.64	0.48	0.04	0.19
Other Postdoc	0.14	0.34	0.00	1.00	0.20	0.40	0.08	0.27
Top US Postdoc	0.23	0.42	0.00	1.00	0.08	0.27	0.35	0.48
Top UK Postdoc	0.21	0.41	0.00	1.00	0.41	0.49	0.04	0.19
UK PhD	0.43	0.49	0.00	1.00	0.86	0.35	0.05	0.21
US PhD	0.50	0.50	0.00	1.00	0.05	0.22	0.90	0.30
Other PhD	0.07	0.26	0.00	1.00	0.09	0.29	0.05	0.23
Assistant Professor	0.22	0.42	0.00	1.00	0.23	0.42	0.22	0.41
Associate Professor	0.25	0.43	0.00	1.00	0.33	0.47	0.18	0.39
Full Professor	0.49	0.50	0.00	1.00	0.39	0.49	0.58	0.49
Firm	0.01	0.08	0.00	1.00	0.01	0.07	0.01	0.09
Research Hospital	0.00	0.06	0.00	1.00	0.00	0.00	0.01	0.09
PRO	0.02	0.15	0.00	1.00	0.04	0.20	0.01	0.08
University	0.97	0.18	0.00	1.00	0.95	0.21	0.98	0.15
Co-I Control	0.06	0.23	0.00	1.00	0.12	0.32	0.00	0.00