The Impact of Industry Collaboration on Research: Evidence from Engineering Academics in the UK*

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August 2010

Abstract

We study the impact of university-industry research collaborations on academic output, in terms of productivity and direction of research. We report findings from a longitudinal dataset on all the researchers from the engineering departments in the UK in the last 20 years. We control for the endogeneity caused by the dynamic nature of research and the existence of reverse causality. Our results indicate that researchers with industrial links publish significantly more. Productivity, though, is higher for low levels of industry involvement. Moreover, growing ties with the industry skew research towards a more applied approach.

Keywords: industry-science links, research collaborations, basic vs. applied research. JEL codes: O3, L31, I23

*The authors express their gratitude to Michael Ben-Gad, Ines Macho-Stadler, Alistair McGuire, Gabriel Montes-Rojas, Markus Perkmann, Dan Peled, Jo Seldeslachts and seminar participants at City University, University of Sheffield, Univeristy of Munich, DRUID conference (Copenhagen), Jornadas de Economía Industrial (Reus), ASSET conference (Istambul) and MOVE workshop on R&D and Technology Tranfer (Barcelona) for helpful comments and criticisms and the Engineering and Physical Sciences Research Council, the National Science Foundation and the European Patent Office for providing the data. We also thank Kamil Dabrowski for excellent research assistance. Financial support from the Pump priming fund at City and ESRC research grant RES-000-22-2806 is gratefully acknowledged.

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1 Introduction

In a modern economy it is essential to transform scientific research into competitive advantages. In the US, extensive collaboration between universities and industry and the ensuing transfer of scientific knowledge has been viewed as one of the main contributors to the successful technological innovation and economic growth of the past three decades (Hall, 2004). At the same time, the insufficient interaction between universities and firms in the EU is, according to a report of the European Commission (1995) itself, one of the main factors for the poor commercial and technological performance of the EU in high-tech sectors.

Nowadays, increasing the transfer of knowledge from universities to industry is a primary policy aim in most developed economies. In the 1980s, spurred by the so-called competitiveness crisis, the US introduced a series of structural changes in the intellectual property regime accompanied by several incentive programs, designed specifically to promote collaboration between universities and industry (Lee, 2000).[1] Almost 30 years on, many elements of the US system of knowledge transfer have been emulated in many other parts of the world.[2]

The increased incentives (and *pressures*) to collaborate with industry have controversial side effects on the production of scientific research itself. Nelson (2004) argues that industry involvement might delay or suppress scientific publication and the dissemination of preliminary results, endangering the "intellectual commons" and the practices of "open

[1] As documented by Poyago-Theotky et al. (2002) the US passed during the 1980s: (i) the Bayh-Dole act (1980) that allowed universities to own and license patents emanting from federally funded research; (ii) the National Cooperative Research Act (1984) that reduced antitrust penalties from engaging in research joint ventures; (iii) the Omnibus and Trade and Competitiveness Act (1988) that established the Advanced Technology Program, which supports collaborative research projects in generic technologies. During this decade, the National Science Foundation also substantially increased the funding for University-Industry Cooperative Research Centers.

[2] The UK Government, for example, published in 1993 a White Paper on Science, Engineering and Technology, which set out a strategy to improve welfare by exploiting the UK strengths in science and engineering.

science" (Dasgupta and David, 1994). Florida and Cohen (1999) claim that industry collaboration might come at the expense of basic research: growing ties with industry might be affecting the choice of research projects, "skewing" academic research from a basic towards an applied approach.

Faculty contributing to knowledge and technology transfer, on the other hand, maintain that industry collaboration complements their own academic research by securing funds for graduate students and lab equipment, and by providing them with ideas for their own research (Lee, 2000). Financial rewards might even have a positive impact on the production of basic research because basic and applied research efforts might be complementary (Thursby et al., 2007) or because they might induce a selection of riskier research programmes (Banal-Estañol and Macho-Stadler, 2010).[3]

These claims bring forward two questions for empirical research: (1) Does collaboration with industry affect researchers' productivity in terms of publication rates? (2) Does collaboration with industry shift the focus away from basic research? Previous research has investigated these questions using patents and licensing and the formation of start-up companies as measures of industry collaboration (see Geuna and Nesta, 2006, and Baldini, 2008, for recent reviews).[4] Many papers, however, have stressed the relatively small role of the commercialisation of intellectual property rights relative to other channels of knowledge transfer. Collaborative links through joint research, consulting or training arrangements are far more important transmission channels for the industry than patents, licenses and spin-offs (Cohen et al. 2002). Academics believe that patents account for less than 10% of the knowledge transferred from their labs (Agrawal and Henderson, 2002). Contract research or joint research agreements are far more widespread (D'Este and Patel, 2007), especially in Europe (Geuna and Nesta, 2006). Possibly due to the

[3] This debate has now reached society at large. Many public channels, including the BBC (through the BBC Radio 4 programme 'In Business', October 13, 2005), The Guardian (August 5, 2005 and January 27, 2007), The Observer (April 4, 2004), have addressed the consequences of increased university-industry collaborations.

[4] A different strand of literature has studied the effects of university spillovers and industry-science links on firm performance (Jaffe, 1989, Cassiman et al. 2008).

lack of comparable data, though, we still know very little about the impact of more collaborative forms of university-industry interactions.

To fill this gap, we compiled a unique, longitudinal dataset containing academic research output (publications), research funds and patents for all the academics that were employed at all the Engineering Departments of 40 major UK universities between 1985 and 2007. We concentrate on the engineering sector, as it has traditionally been associated with applied research and industry collaboration and it contributes substantially to industrial R&D (Cohen et al. 2002). Comparing the effect of grants with and without industry partners, we can identify the individual impact of industrial collaboration on academic productivity. Following the academics over time we are also able to control for individual characteristics, potential reverse causality problems, and the dynamic effect of publications. Moreover, since our dataset contains the majority of academic engineers in the UK, our results are not driven by the most successful researchers, those at a single university, or academic inventors alone.

As a first contribution, we uncover two countervailing effects in the impact of collaborative research on academic research output. Researchers with no industry involvement are predicted to publish less than those with a small degree of collaboration. Nevertheless, higher levels of industry involvement negatively affect research productivity. Therefore, the *existence* of industry partners is positive but the *intensity* of industry collaboration is negative. The predicted publication rate of an academic with an average level of collaboration is higher than that of an academic with no collaborative funding. But, for higher levels of collaboration, the predicted number of publications turns out to be lower, and can even be lower than for those with no funding at all.

We show that it is key to take into account the inherent endogeneity problems caused by the dynamic effects and the existence of reverse causality. As shown by previous papers (e.g. Arora et al. 1998, Agrawal and Henderson, 2002), past, present and future publications are correlated. If one does not include past publications in the regression, industry collaboration would capture the positive effects of past productivity and it would appear to be unambiguously good. But if one includes lags of the dependent variable, there are endogeneity problems. Further, successful, productive researchers are better placed to attract interest from industry. Industry collaboration can be the consequence, and not just the cause, of high numbers of publications. We therefore use a dynamic panel data estimation method in which the lagged dependent variable and other endogenous variables are instrumented for.

Our results bolster empirical evidence from previous surveys and cross-sectional studies by establishing a causal relationship between collaborative research and academic output. Some survey studies suggest that industry involvement is linked to higher academic productivity (e.g. Gulbrandsen and Smeby, 2005).[5] Once controlling for endogeneity, we still find supportive evidence for the positive impact of the presence of collaboration on research output. The negative effect of the intensity of collaboration is also consistent with other survey results (Blumenthal et al., 1986) and cross-section empirical evidence (Manjarres-Henriquez et al., 2009). We are only aware of one (two-period) panel study that is able to control for individual characteristics: Goldfarb (2008) documents a decrease in the academic output from 1981-1987 to 1988-1994 for the average researcher in a sample of 221 university researchers repeatedly funded by the NASA.[6]

The second main contribution of this paper is to show that industry collaboration has a negative effect on the number of basic research articles while it increases the more applied type of research publications. These results are consistent with the "skewing" effect of industry involvement on direction and focus of research pointed out by questionnaire data studies. Blumenthal et al. (1986) and Gulbrandsen and Smeby (2005), for example, report that the choices of research topics of academics whose research is supported by industry were biased by their commercial potential. Instead, the empirical papers using patenting and licensing as measures of industry involvement fail to find evidence of a negative effect of patenting on the number of basic publications (Breschi et al., 2008; Calderini et al. 2007; Hicks and Hamilton, 1999; Thursby and Thursby, 2002, 2007; van Looy et al.,

[5] As argued by Blumenthal et al. (1986), "the most obvious explanation for this observed relation [...] is that companies selectively support talented and energetic faculty who were already highly productive".

[6] The NASA, despite not being an industrial partner, is a very programmatic, mission-oriented government agency.

2006).[7] We believe that our findings are the first to firmly establish the presence of a "skewing" effect.

The third contribution of this study is to compare and separate out the effects of collaboration sponsored through research grants with industrial partners from the effects of patenting. After controlling for the dynamic nature of the publication process and the endogeneity of partnerships with the industry, we find that patenting does not hinder or delay the publication of research results but does not affect it positively either. These findings diverge from most recent empirical studies suggesting a positive relationship between patenting and publication rates (Azoulay et al., 2009; Breschi et al., 2008; Calderini et al. 2007; Fabrizio and DiMinin, 2008; Stephan et al., 2007; van Looy et al., 2005).[8] Our results are most consistent with those of Agrawal and Henderson (2002), who found that patenting did not affect publishing rates of 236 scientists in two MIT departments in a 15-year panel, and those of Goldfarb et al. (2009) who report similar results for the effect of licensing on the number of publications for 57 inventors at Stanford University in an 11-year panel.

The paper is organised as follows. In section 2 we describe the dataset and introduce our empirical strategy. Section 3 presents our main results, discussing in detail the problem of endogeneity. Section 4 discusses and concludes.

[7] Thursby and Thursby (2002), for example, conclude that changes in the direction of faculty research seem to be relatively less important than other factors in explaining the increased licensing activity. Thursby and Thursby (2007), as Hicks and Hamilton (1999) earlier, find no systematic change in the proportion of publications in basic versus applied journals between 1983 and 1999.

[8] Fabrizio and DiMinin (2008), for instance, found a positive effect of researchers' patent stocks on publication counts in a sample of 166 academic inventors as compared to a matched set of non-patenting scientists. Azoulay et al. (2009) observe that both the flow and the stock of scientists' patents are positively related to subsequent publication rates without comprising the quality of the published research.

2 Empirical Strategy

2.1 Data

We created a unique longitudinal dataset containing demographic characteristics, publications, research funds and patents for all researchers employed at the Engineering Departments of 40 major UK universities between 1985 and 2007 (see Table 1 for a list of universities). Starting from all universities with engineering departments in the UK, we discarded those for which university calendars providing detailed staff information were available for less than five years. Our final sample contains 40 major universities, including all the 19 universities that are members of the prestigious Russell Group, a coalition of research intensive UK universities, as well as 21 comprehensive universities and technical institutions.

We retrieved names and academic ranks of university researchers from university calendars.[9] We focused on academic staff carrying out both teaching and research and did not consider research officers or teaching assistants. Whenever possible, we obtained full names (first and last name), when not possible, we had to record last names with the two initials of the first name. We followed the researchers' career paths between the different universities in our dataset.[10] Academics leave (and join or rejoin) our dataset at different stages in their career, when they move to (or from) abroad, industry, departments other than engineering (e.g. chemistry, physics, computer science), or universities not part of our dataset. In total we collected 7,707 individuals, 5,172 of which remain in our dataset for six years or more. They represent the basis for our data collection and enable us to retrieve information on publications, research funds and patents.

[9] University calendars and prospectuses are available through the British Library, which by Act of Parliament is entitled to receive a free copy of every item published in the United Kingdom. This data was supplemented with information from the Internet Archive. The Internet Archive is a not-for-profit organisation maintaining a free Internet library, committed to offering access to digital collections. Their collection dates back to 1996 and enabled us to retrieve information from outdated Internet sites.

[10] This was done by matching names and subject areas and checking websites of the researchers.

Publications. Data on publications was derived from the ISI Science Citation Index (SCI). The number of publications in peer-reviewed journals even if not the only measure is the best recorded and the most accepted measure for research output as publications are essential in gaining scientific reputation and for career advancements (Dasgupta and David, 1994). We collected information on all the articles published by researchers in our database while they were employed at one of the 40 institutions in our sample. Most entries in the SCI database include detailed address data that allowed us to identify institutional affiliations and unequivocally assign articles to individual researchers.[11]

Research funds. The information on industry collaborations are based on grants given by the Engineering and Physical Sciences Research Council (EPSRC), the main UK government agency for funding research in engineering and the physical sciences. Each award holds information on research collaborators, and grants with one or more industry partner are considered "collaborative grants". As defined by the EPSRC, "Collaborative Research Grants are grants led by academic researchers, but involve other partners. Partners generally contribute either cash or 'in-kind' services to the full economic cost of the research." The EPSRC encourages research in collaboration with the industry. As a result, around 35% of EPSRC grants presently involve partners from industry. The volume of EPSRC grants with industry partners cannot be taken as a proxy for direct funding from the industry. But, since the EPSRC is by far the largest provider of funding for research in engineering (amounting to around 50% of overall funding), these mediated partnerships allow for a very comprehensive (and homogeneous) insight into the dynamics of university-industry collaborations. Our database contains information on start year and duration of the grant, total amount of funding, names of principal investigators and coinvestigators, institution of the principal investigators (the grant receiving institution), and names of partner organisations. Data on these grants is available from 1986 onwards.

[11] Publications without address data had to be ignored. However, we expect this missing information to be random and to not affect the data systematically.

Patents. Patent data was obtained from the European Patent Office (EPO) database. We collected those patents that identify the aforementioned researchers as inventors and were filed while they were employed at one of the 40 institutions. We not only consider patents filed by the universities themselves but also those assigned to third parties, e.g. industry or government agents. The filing date of a patent was recorded as representing the closest date to invention. Since the filing process can take several years, we were only able to include patents awarded by 2007, hence filed before 2005.[12] The EPO covers only a subsample of patents filed with the UK Intellectual Property Office (UKIPO). Nevertheless, those patents that are taken to the EPO may probably be those with higher economic potential and/or quality (Maurseth and Verspagen, 2002).

Sample. Limited information on patents and grants reduced our sample period to 1986-2004. We further excluded all inactive researchers (those with neither publications, patents or funds during the entire sample period). This left us with a final sample consisting of 4,066 individuals, with 44,722 year observations, 75,380 publications, 29,347 research projects, and 1,828 patents.

2.2 Variables and Descriptive Statistics

In this section we define the variables used to estimate our models. We created measures of research output, research collaboration, patents, and time variant and time invariant control variables. Russell Group universities are considered research intensive institutions and attract most of the UK's research funding, we therefore display all summary statistics separately for researchers at universities belonging to the Russell Group and for researchers that are not.

[12] Just like previous studies (see e.g. Fabrizio and DiMinin, 2008), data construction requires a manual search in the inventor database to identify the entries that were truly the same inventor and to exclude others with similar or identical names. This was done comparing address, title and technology class for all patents potentially attributable to each inventor. The EPO database is problematic in that many inventions have multiple entries. It was therefore necessary to compare priority numbers to ensure that each invention is only included once in our data.

Research output. As a measure of research output, we consider the normal count of publications (the number of publications for which the researcher is an author) in accordance with the majority of studies on industry collaboration. However, publication counts might be misleading for articles with a large number of authors and may not reflect a researcher's effective productivity. We therefore additionally obtain the "co-author-weighted" count of publications for which we weight a publication associated to an academic by the inverse of the publication's number of coauthors.[13]

To investigate the question whether researchers with links to industry publish articles of lower quality we use the "impact-factor-weighted" sum of publications (with the weights being the impact attributed to the publishing journal) as an additional proxy of academic publishing activity. To do so, we use the SCI Journal Impact Factor (JIF), a measure of importance attribution based on the number of citations a journal receives to adjust for relative quality. Though not a direct measure for quality, the JIF represents the importance attributed to a particular article by peer review. As the JIF of journals differs between years, and journals are constantly added to the SCI, we collected JIFs for all the years 1985-2007, to capture all SCI journals and to allow for variation in the impact factor.

Figure 1 shows that the average number of publications per staff was rising continuously over the sample period, in both the Russell Group and the Non-Russell Group of universities.[14] Table 2 shows the all-time averages and the differences between the two groups of universities and it shows that the average number of publications per member of staff per year is significantly higher for the elite Russell Group of universities (1.67 vs. 1.10). The difference in publications between the Russell Group universities and the rest stays significant even after we take into account the number of coauthors (0.61 vs. 0.42) or we adjust for quality (1.77 vs. 0.97).

[13] Formally, the coauthor weighted count of a researcher i in year t is given by $\sum_{p=1}^{Pub_{it}} \frac{1}{Coa_{itp}}$, where Pub_{it} is his number of publications in that year and Coa_{itp} is the number of coauthors of an article p.

[14] Several papers have documented a trend towards increasing multi-coauthorship (see Katz and Martin, 1997), but, even after we control for the number of coauthors we still find that the publication count has at least tripled between 1985 and 2007.

As an indicator of the direction of research we use the Patent board (formerly CHI) classification (version 2005), developed by Narin et al. (1976) and updated by Kimberley Hamilton for the National Science Foundation (NSF). Based on cross-citations matrices between journals, it characterises the general research orientation of journals, distinguishing between (1) applied technology, (2) engineering and technological science, (3) applied and targeted basic research, and (4) basic scientific research. Godin (1996) and van Looy et al. (2006) reinterpreted the categories as (1) applied technology, (2) basic technology, (3) applied science, and (4) basic science; and grouped the first two as "technology" and the last two as "science". Due to the applied character of engineering science, categories 1 and 2 represent 27% and 46% of all publications whereas category 4 only represents 7% of the articles in our sample.

Collaborative research and patents. Principal investigators and coinvestigators on sponsored projects are understood to contribute to the research project and benefit from generated outcomes. To account for the participation of all investigators, we divided the total monetary income from the research grants between the principal investigator (PI) and her named coinvestigator(s). Although we include coinvestigators as beneficiaries of the grant, we positively discriminated PIs by assigning them half of the grant value and splitting the remaining 50% amongst their coinvestigators. PIs are assigned a major part of the grant as they are expected to be responsible for the leadership of the research and to profit most from a successful partnership. We additionally spread the grant value over the whole award period, i.e., if the grant is 2 years we split it equally across those 2 years, if it is over 3 or more years, the first and the last years (which are assumed to not represent full calendar years) receive 25% each, the remaining 50% is split equally across the intermediate years.[15] This is done in order to account for the ongoing benefits and implications of a project and to mitigate against the effect of focusing all the funds at the

[15] Formally, if $Fund_{i,s,d,f}$ is the monetary value of a grant f received by researcher i with start year s and duration d, the value of the grant assigned to a year t is: (i) for $d = 1$, $Fund_{i,s,d,f}$ when $t = s$; (ii) for $d = 2$, $\frac{Fund_{i,s,d,f}}{2}$ when $t = s$ and $t = s + 1$; and, (iii) for $d > 2$, $\frac{Fund_{i,s,d,f}}{2(d-1)}$ when $t = s$ and $t = s + d - 1$ and $\frac{Fund_{i,s,d,f}}{d-1}$ when $s < t < s + d - 1$.

start of the project.

We use a 5-year window to calculate the stock of "accumulated" collaboration to better capture the "permanent" profile of an academic. We constructed two time-variant dummy variables, which allow for a differential effect for researchers who received funding that did not involve industry collaboration, and for researchers who collaborated with industry in the 5 years preceding the publication. Since our objective is to evaluate not only the influence of the *existence* of industry partners but also the *intensity* of collaboration activity, we also compute the fraction of funds with one or more industry partners over all EPSRC funds.

Figure 2 reports the percentage of industry collaboration and shows that the two groups of universities do not seem to differ much. Table 2 reveals that these differences, no matter how small, are still significant and on average the percentage of industry collaboration is slightly higher (33% vs. 31%) for Russell Group universities. Figure 2 gives evidence of a sudden increase in industry partnerships in the mid-1990s and a stagnation in recent years, which affected all UK universities equally. This might imply severe changes in funding allocation through the UK research councils following the government's White Papers from 1991 and 1993, which outlined changes in the structure of funding and higher education.

As mentioned above, we aim to separate the effect of patenting from the effect of industry collaboration. To measure the impact of academic patenting on timing and rate of publications, we use the number of patents filed during the same year and the two years preceding the publication. Researchers in Europe, unlike the US, cannot benefit from a "grace period" and hence they have to withhold any publication related to the patent until the patent is filed. Publications might be released once the patent is filed. We therefore expect a lag of up to 2 years between invention and publication in a journal. We can see from Table 2 that the average number of patents differs significantly between the two groups of universities (0.04 vs. 0.03). The values are very small for both groups but the average number of patents filed by researchers has increased substantially over the past 20 years and in particular after 1995 (from 0.03 in 1985 to 0.06 in 2003).

Control Variables. Research productivity and collaborative activity might be linked to the researchers' personal attributes such as sex, age, education and academic rank. Some of these attributes, however, do not vary over time and therefore they do not play a role in the dynamic variation, which is the focus of this paper. *Academic rank* is the only time-variant observable characteristic in our dataset. Thus we incorporate information on the evolution of researchers' academic status from lecturer to senior lecturer, reader and professor into our analysis. Lecturer and senior lecturer correspond to the assistant professor in the US, whereas reader would be equivalent to associate professor. *Year* dummies are included in all regressions to control for time effects in our panel.

Interaction Variables. The effect of industry collaboration on research output might additionally differ for different types of academics. We therefore interact our measures of industry collaboration with several categories of individuals in some of our models.

Firstly, since the descriptive statistics above show significant differences between the two types of universities, we interact membership to the *Russell Group* with the measures of industry collaboration. Most of the previous literature on the impact of industry collaboration (e.g. Agrawal and Henderson, 2002, Thursby and Thursby, 2007) only use data on researchers at top universities (in terms of research or patents). However, the benefits and costs of collaborative projects differ depending on the institutional culture (Owen-Smith and Powell, 2001; Levin and Stephan, 1991) and might therefore lead to differential impact of industry collaboration on publication outputs. For the UK, Geuna (1997) finds that universities with small science, engineering or medical departments publish fewer papers and receive less grants than other universities, but that a larger share of these grants comes from industry.

Secondly, several papers have argued that the most able researchers, which in this paper we label as *stars*, may differ considerably from the rest of academia in that they are more able to combine academic and commercial research. Publication *stars* are not only found to collaborate more with industry, but they also produce more patents (Zucker and Darby, 1996; Stephan et al. 2007). However, they also have plenty more opportunities to conduct their research and do not need to adjust to specific societal needs (Goldfarb, 2008). We hence expect the impact of industry collaboration to differ for these *stars*. As *stars* we define all those researchers that are on the top 25 percentile of research productivity, with an average of 2 or more articles per year.

Thirdly, the impact of industry partnerships on the publication behaviour of senior academics, who have more experience and an established network of research partners, may differ from that of younger researchers, who pursue publications to further their career (Dasgupta and David, 1994). The changes in university culture and the increasing emphasise on collaboration, however, have been recent developments and it might be that researchers at the start of their career best adjust to these new requirements. We therefore create a binary variable that determines whether the researcher is at the start (lecturer or senior lecturer) or at a later stage of her career (reader or professor).

2.3 Empirical Model

We base our empirical specification on the implicit assumption that the utility of an academic in a given year depends on her academic reputation and status, which are determined by the stream of academic research output (past and present publications in peer-reviewed journals), on the amount of research grants generated (research council funds), and on commercial output (number of patents). Publications, grants and patents are directly linked to how much time or effort the academic devotes to research, to collaboration with industry, and to teaching and other activities. The time devoted to collaboration with the industry may pose a trade-off for academic research output, as it might provide new ideas but also crowd out time for research.

The optimal time allocation problem for the academic consists of choosing the utility maximising fraction of time she devotes to each activity. The associated first-order conditions involve first derivatives of the utility function with respect to the time devoted to research and to collaboration with industry. Thus, for any utility function which is not linear in publications, the first order conditions define an implicit function by which publications can be expressed as a function of the relative time dedicated to collaborate with industry. This function will of course be conditional to time-variant and invariant socio-demographic characteristics of the academic, and past publications.

To estimate how collaboration with the industry affects research output, we estimate a dynamic model where current publications are influenced not only by past publications but also by the degree of collaboration with industry. We choose a specification that allows current publications to be affected by the existence and the intensity of collaborative funding. To do so, we include a dummy for having had any type of EPSRC past funding in the last five years, another dummy for having had EPSRC funding with industry partners, and then a variable that measures which fraction of the overall funding was joint with industry. By including a dummy (intercept) and a continuous variable (slope), we intend to capture the trade-off of industry collaboration on publications described above.[16]

Accordingly, we formulate our reduced form equations as:

$$\ln y_{it} = \beta_0 + \sum_{j=1,2} \alpha_j \ln y_{i,t-j} + \beta_1 f_{it} + \beta_2 indf_{it} + \beta_3 \ln indint_{it} + \sum_{k=1,2,3} \gamma_k p_{it-1-k} + \delta x'_{it} + \mu_i + v_{it}$$

where y_{it} represents academic i's research output at time t, β_0 a constant, f_{it} is an indicator variable for having received any kind of EPSRC funds; $indf_{it}$ is an indicator variable for having received EPSRC funding with industry partners; $indint_{it}$ measures the *intensity* of the collaboration with industry; p_{it}, are indicator variables for having filed patents; and x_{it} is a vector time-variant explanatory variables including tenure rank. Note that the constant and the two dummies need not be collinear as they are not exclusive. The parameters β_0, β_1, and β_2 capture the incremental effect of different sources of funding. An academic with no funding at all will only have a constant term equal to β_0, one academic with non-industrial EPSRC $\beta_0 + \beta_1$, and, one academic with EPSRC grants with the industry $\beta_0 + \beta_1 + \beta_2$. Since the distribution of grants and academic research output has been found to be highly skewed (D'Este and Fontana, 2007), we take logarithms of both measures. The error term contains two sources of error: the academic i's fixed effect term μ_i, and a disturbance term v_{it}. Thus, our specification corrects for the fact that

[16] A specification with an intercept and a linear term fits our data better because the researchers with no collaborative grants at all are substantially different from those with a very small percentage of collaborative grants.

industry collaboration, patents, past publications and academic rank may be endogenous. Publishing, being a professor or getting a lot of industry funds, for example, are correlated with having a high cognitive ability, which is unobserved.

Still, although the fixed idiosyncratic disturbances μ_i are uncorrelated across individuals, they create autocorrelation of the errors over time. To ensure consistency and to solve the fixed effects induced autocorrelation of our estimates, we estimate these models using the GMM based Arellano-Bond estimator (Arellano and Bond 1991; Blundell and Bond 1998). In brief, this estimator treats the model as a system of equations – one for each time period – where the predetermined and endogenous variables in first differences are instrumented with suitable lagged variables. To further improve the efficiency of our estimates, we use the two-step GMM based on taking deeper lags of the dependent variable as additional instruments, as described in Roodman (2006). The two-step standard errors tend to be downward biased and we therefore calculate Windmeijer corrected standard errors (Windmeijer, 2005). We treat the lagged number of publications, the number of patents, the variables for the degree of industry collaboration, the collaboration dummies and the academic rank as endogenous. The year dummies are treated as exogenous and are used as instruments. Finally, we use department size as an additional exogenous instrument.

We also report GLS with fixed effects, and GMM estimations treating industry collaboration and/or patents as exogenous variables in order to illustrate the importance of correcting for reverse causality of industry collaboration and past realisations of research output when trying to estimate the true impact the former on the latter.

3 Empirical Results

In this section we present our estimates on the impact of industry collaboration on research productivity. We first introduce our main results, comparing the estimates of our benchmark model with those of alternative regression models. Then, we show how the impact of research collaboration and patents on research productivity differs across types of researchers. Finally, we show how robust results are if we use alternative measures of research productivity.

3.1 Main Results

Table 3 reports the estimates of research productivity measured as the total number of publications using four different model specifications. While the first model uses a GLS with fixed effects estimator, specifications 2, 3 and 4 are estimated using two-step difference GMM. In specification 2 industry collaboration and patents are treated as exogenous explanatory variables. In the third column, industry collaboration terms are instrumented as endogenous variables while patents are still considered exogenous. Finally, in the fourth model, which we consider to be our benchmark, all the explanatory variables except for the year dummies are treated as endogenous. For all GMM specifications, we report the Arellano-Bond test and the Sargan/Hansen test at the bottom of the table. In the following paragraphs we present the main results grouping them in themes for clarity.

Baseline and past publications: In all specifications, the exponent of the estimate of the constant term can be considered as the "baseline" productivity prediction, i.e. the expected number of publications for a lecturer who does not have any previous funding or previous patents. This baseline prediction for the number of publications ranges from 1.57 articles per year in the GLS specification to 1.36 in the benchmark GMM model (1.57 and 1.36 are the antilogs of 0.453 and 0.308, respectively). Note that the baseline number of publications decreases when we include the logarithm of the lagged number of publications (GMM columns). We interpret this fact as an indication that the constant term in the GLS specification was capturing the omitted lagged publications' effect.

The strong statistical significance of the lagged publications in the GMM specifications in Table 3 shows that it is important to take into account the dynamic nature of the publication process and thus use GMM as opposed to GLS. In all GMM specifications, the coefficients associated with the lagged publications are positive and, although the first lag is insignificant, the second lag is highly significant throughout. Because we have taken logarithms of both the dependent variable and its lagged terms, we can interpret these coefficients as elasticities. Thus, according to benchmark specification results, increasing by 100% (i.e. doubling) the number of publications two years prior will increase the expected number of current publications by 4.95%.

Having had funding: As expected, the existence of any funding in the last five years enhances research productivity in all four specifications. In the GLS specification the "had some funding" coefficient is significant and equals 0.0309, indicating that if an academic had received funding she publishes, on average, around 3% more articles than if she had not received any funding at all. If we take into account the dynamic nature of the publishing process but not the fact that industry collaboration and patents may be endogenous (second column's specification), funding does not have any significant impact on the number of publications. However, as soon as we take into consideration that funding and collaboration are endogenous (columns three and four), the coefficient becomes significant again.

Having collaborated with industry: More importantly, if some of this past funding involved partners from industry, the average number of publications increases by a further 4% in the GLS regression. As a result, an academic collaborating with industry would publish 7% more articles than one who did not receive any funding at all. As in the previous case, in the benchmark specification, in which we take into consideration the dynamics and the endogeneity problems (column four), the coefficient is larger.

Intensity of industry collaboration: The coefficient associated with this variable can be interpreted as an elasticity as we measured it as the logarithm of the fraction of EPSRC grants with the industry. Although it is insignificant for the first two specifications, this elasticity is significant and negative in the last two specifications. Thus, there is a discrete positive impact of collaborating with industry, but the more an academic collaborates with industry, the less she publishes.

To summarise, and drawing from the benchmark specification in the last column, a lecturer without funding in the last five years is predicted to publish 1.36 articles per year. If she had obtained funding but did not collaborate she would be predicted to publish 14% more publications or up to 1.57 publications. If part of the funding had been with industry partners, she would see her publications increase by an additional 11%, up to 1.78. Thus, having collaborated with industry would mean that she is expected to publish 25% more than if she had not received any funding at all. However, as the level of collaboration with industry increases, by say 10%, the predicted number of publications decreases by 2.66%.

In Figure 3 we illustrate the impact of industry collaboration on publications with a plot of the predicted number of publications for a lecturer with no patents for different levels of intensity of industry collaboration. The levels of collaboration with industry range from 0% to 100%, i.e., from no funding involving industry partners to all funding involving industry partners. A lecturer collaborating with industry is expected to publish 1.78 publications in a given year, but the larger the intensity of her collaboration with industry, the less she is expected to publish. At 33% of funds in collaboration with industry, or the sample average, the predicted number of publications is still above 1.57, and thus higher than if she did not collaborate with industry. At 38.5% of collaboration intensity, the predicted number of publications matches exactly the number for non-collaborative funding. Finally, if the percentage of her collaborative funding is 81.8%, the predicted number of publications is lower than if she had not received any grants in the previous 5 years. At even higher levels of collaboration intensity she is expected to publish less than 1.36 articles per year.

Patents: Consistent with the recent literature, filing a patent in the current year, and in each of the two previous observation periods increases the number of publications in the GLS specification (column one). The number of current patents and those in the year before the last (t and $t-2$) increase the number of articles by about 2% each. However, when we correct for the dynamic effect of publications using GMM, the signs turn negative. If we assume that past publications and rank are endogenous and collaboration and patenting exogenous (column two), the coefficients associated to patents are all insignificant. When we add industry collaboration to the set of endogenous variables, current and past patents are significant and have a negative effect on publications (column three). Finally, in our fourth -benchmark- specification which also takes into account the endogeneity of patents, all patent variables are insignificant. The release of patents hence has no influence on publications as soon as we correct for endogeneity.

Academic Rank: We can also observe differences between the GLS and the GMM specifications with respect to the effect of academic rank. In the GLS regression, later career stages are associated with higher number of publications. All senior ranks (senior lecturer, reader and professor) publish significantly more than the omitted junior category (lecturer). Moreover, being a professor has a stronger effect than being a reader, which in turn has a stronger effect than being a senior lecturer. In the GMM regressions, on the other hand, the effect of being a professor is lower than that of being a senior lecturer or a reader, although it is still significantly positive. Readers seem to be those who publish most, followed by senior lecturers, professors and lecturers, respectively. Hence, after allowing for endogeneity of research output, which is linked to tenure promotion, we find evidence for reduced productivity over the career life-cycle (Levin and Stephan, 1991).

Goodness of fit: With respect to goodness of fit of the GMM models, the Arellano-Bond tests (reported at the bottom of Table 3) do not reject the null that there is absence of second (or higher) order correlation of the disturbance terms of our specifications, which is required for consistency of our estimates. The Sargan and Hansen tests are also insignificant suggesting that the models do not suffer from over-identification.

3.2 Differences across Academics

In Table 4 we present the estimates of model specifications that interact researchers' characteristics with our variables of interest, that is, industry collaboration and patents. For simplicity, we present the main and interacted effects estimates in two columns. The first column of each block (main effect) corresponds to the researchers in the groups described in the column header, the second column (interaction effect) corresponds to the estimates of the comparison group.

In the first specification we separate out the effects of academics belonging to the elite group of universities (Russell Group) from the academics at other universities. Despite the dissimilarities in terms of descriptive statistics, the effect of industry collaboration on publications does not differ significantly between the two groups of universities in our sample. The estimates and the levels of significance for the Russell Group academics do not differ substantially from those in our benchmark model in column four of Table 3 except for the estimates associated to the number of filed patents. For academics at a Russell Group university the estimates for the patent variables turn negative and the effect of the number of patents filed the previous year becomes significant (-0.201, equivalent to a reduction of 20% in publications). Although statistically not significantly different, the effect of patents is more positive for academics at universities that are not members of the Russell Group.

The second block of regressions presents the estimates of the effect of industry collaboration and patents for the *star* researchers, academics in the top 25 percentile in terms of average publication numbers, which in our sample is an average of 2 or more publications per year. As in the previous regression, we observe that the estimates for *stars* are similar to the average estimated in the benchmark model in Table 3. The estimates for the academics not categorised as *stars* do not differ from the non-stars significantly either. Hence, both regressions suggest that the effect of knowledge transfer on publication productivity does not differ by the level of prestige, whether that of the academic or that of the university.

Looking at the third block of results, we can see that the coefficients for senior staff (readers and professors) are larger than in the benchmark model and that they differ significantly from the coefficients for junior academics (lecturers and senior lecturers). Firstly, the impact of having received funding on the number of articles is more positive for senior academics (0.390, equivalent to an increase of 39% of the constant) as is collaboration with industry (0.163 equivalent to a further 16%). Also, the effect of the intensity of a researcher's involvement in collaborative research is more negative than that of the benchmark (elasticity of -0.729). Junior staff on the other hand benefit less from research funding, which indicates that less experienced members of staff are less able to transform funding into research output in terms of publications. Their number of publications, however, decreases far slower as the fraction of grants involving industry partners increases.

3.3 Weighted Number of Publications

Table 5 contains the estimates of variations of the benchmark model as a robustness check exercise. Instead of the natural count of publications, we model the number of publications weighted by the number of coauthors and the quality of the publishing journal.

All the coefficients have the same sign as in the benchmark regression in Table 3. Their magnitude, however, is smaller and some of the effects of funding and collaboration become insignificant. Receipt of funding, with and without the industry, does not significantly affect the number of publications if they are weighted by the number of coauthors. The intensity of collaboration still has a significant and negative effect. Therefore, industry collaboration has a more damaging effect on coauthor weighted publication counts than in the normal count of publications.

Instead, if publications are weighted by the impact factor, the intercepts associated with receipt of funding and collaboration are positive and significant. The coefficients are very similar to those of the benchmark regression in Table 3. The estimate of the intensity of collaboration is rather, much smaller and insignificant. Therefore, collaboration with industry increases is better in terms of quality of the publications.

Interestingly, when weighting publications by the number of coauthors, professors no longer publish more than lecturers. Academics tend to publish with an increased number of coauthors as they progress in the academic rank and although the count of publications is significantly greater, the weighted average is not. Nevertheless, when adjusting publications by quality, the effect of the professor dummy again becomes positive and significant.

3.4 Basicness of Publications

We now disaggregate our results using the patent board classification index. Table 6 reports the estimates for the impact of collaboration and patents on the count of publications in each of the four categories of research journals, “applied technology”, “basic technology", "applied science" and "basic science". The first category is considered the most applied and the last one the most basic.

In all the regressions, except for the fourth specification, the coefficients of collaboration display the same sign as in the benchmark regression in Table 3. But the magnitudes of the coefficients for the two dummies differ substantially across the regressions. The positive effect of the existence of funding is mainly due to an increase in the number of publications in the basic technology category. The positive effect of the existence of collaboration is mainly due to an increase in the number of publications in the applied technology category. The negative effect of the intensity of collaboration, instead, is more widespread. It not only reduces the number of publications in the most applied set, but also in the most basic set of publications.

In sum, funding has a positive impact on technological research (applied technology and basic technology). While funding without industrial partners biases output towards the area of basic technology, funding with industrial partners introduces a bias in publications towards the area of applied technology. Funding alone does not significantly increase the number of publications in applied technology unless it involves partners from industry. The effect of collaboration on this set of publications is indeed more positive than for the aggregate set in the benchmark regression. The positive dummy coefficient is larger and the negative effect of the intensity is lower.

We do not find a positive effect of funding on publications in scientific research journals. For both, applied scientific and basic scientific, the funding dummies do not have a significant effect. The overall effect of the two dummies on the most basic set of publications is negative. However, we do observe significant decreasing numbers of publications for an increasing fraction of industry collaboration. A researcher hence mostly publishes in the scientific research journals if she does not receive any research grants or research grants with no industry involvement.

The release of patents in the current year has a negative effect on the number of publications in basic technology journals. Patenting in the previous year also has a negative effect on publications in applied scientific journals. As these represent the fields of research most closely related to the invention of new technology and hence patenting activity, the negative signs could indeed confirm the secrecy hypothesis and a crowding out of publications in favour of patents.

4 Discussion and Conclusion

This paper studies the effects of research collaborations, a knowledge transmission channel that does not necessarily involve commercialisation. As argued by many authors, research collaborations, contract research, consultancy, and conferences are far more important channels of knowledge transfer than patents, licenses and spin-offs. They are, however, more difficult to measure empirically and even more difficult to compare across institutions and time. Here, we have focused on the effects of research collaborations using homogeneous information on grants awarded by the EPSRC, the by far most important funder of research in engineering sciences in the UK. By comparing individuals who are involved in industry collaboration mediated through these grants with researchers who do not receive funding or do not partner with industry, we are able to identify the effects of collaboration on research productivity.

Our main results for this panel indicate that, on average, researchers benefit from collaborating with industry. Researchers with no industry involvement are shown to publish less than those with a small degree of collaboration. Nevertheless, higher levels of industry involvement negatively affect research productivity in terms of number of publications. Still, the publication rate of an academic with an average level of collaboration is higher than that of an academic with no collaborative funding. But for higher levels of collaboration, the predicted number of publications turns out to be lower. There are, therefore, two countervailing effects: the *presence* of industry partners is associated with a higher degree of academic research output but the *intensity* of industry collaboration decreases academic productivity.

We show that the impact of excessive diversion from academic activity through industry collaboration can be seriously underestimated when an inadequate estimation method is used. As documented in previous research (e.g. Arora et al. 1998, Agrawal and Henderson, 2002), past, present and future publications are correlated. Thus, including lags of the dependent variable creates endogeneity and biases the estimates. Further, successful, productive researchers are better placed to attract interest from industry. Industry collaboration and patents can be the consequence, and not just the cause, of high numbers of publications. We therefore use a dynamic panel data estimation method in which the lagged dependent variable and other endogenous variables are instrumented for.

Without controlling for the dynamic effects, both the existence and the intensity of industry collaboration would appear to enhance the number of publications. But as collaboration and past publications are correlated, the positive effects of past publications would be wrongly attributed to collaboration. When this dynamic effect of the publications is taken into account, the intensity of collaboration no longer enhances academic productivity. Still, if one assumes that collaboration is exogenous, its effect is very small and insignificant. This could be caused by a correlation between industry collaboration and other unobserved time variant factors, such as accumulated ability or experience, which also enhance academic productivity. Once we instrument the industry collaboration, the negative effect of the intensity grows stronger and becomes significant.

To estimate the effect of patents it is again crucial to take into account both the dynamic effect of publications and the endogeneity problem. In a standard fixed effects regression, patents would have a positive and significant impact on the number of publications. This result would be consistent with the more recent evidence on patents (e.g. Fabrizio and DiMinin, 2008, and Azoulay et al., 2009). This positive effect disappears in the dynamic panel data models because the patents no longer capture parts of the effect of past publications. If one considers patents exogenous to publications, the number of patents even has a negative and significant impact on the count of publications. This significance is not confirmed once we control for endogeneity. Indeed, it is possible that patents are positively correlated to an unobserved factor, such as consultancy activity, which is also negatively correlated with publications. Correcting for endogeneity, the patents do not predict publication rates, as already found in Agrawal and Henderson

(2002) and Goldfarb et al. (2009).

Our findings suggest that encouraging universities to collaborate moderately with industry is a beneficial policy. A small degree of industry collaboration not only facilitates the transfer of basic knowledge and accelerates the exploitation of new inventions, but also increases academic productivity. Collaboration, though, promotes applied research and discourages basic research. Collaboration unambiguously increases the publications in the most applied set of journals while it decreases those in the most basic set. Therefore, collaboration might need to be discouraged if basic research output is the desired objective.

We use a large uniquely created longitudinal dataset containing the academic career of the majority of academic engineers in the UK. We concentrate on the Engineering sector because it has traditionally been associated with applied research and industry collaboration and it contributes substantially to industrial R&D (Cohen et al. 2002). In other less applied fields, collaboration might generate fewer ideas for further research and therefore the impact of industry collaboration might be worse. But, the time actually spent collaborating with the industry might also be lower.

Ours can only be a first step in the research of other channels of knowledge transfer. We expect researchers with a high proportion of collaborative EPSRC grants to also have a high proportion of contract research. But it is not clear whether our results would change if the intensity of industry collaboration was measured as the proportion of contract research with respect to total research funding. With more information on different channels of knowledge transfer, we would be better able to make comparisons. Here we have already shown that research collaborations have more impact on research productivity than patents. Further, it might also be interesting to tackle interactions between different knowledge transfer channels. We know very little on whether collaboration channels complement or substitute each other. Consultancy, for example, might have a positive effect on research if it is complemented by collaboration in research. Of course, this is only a conjecture and a challenging task for future research.

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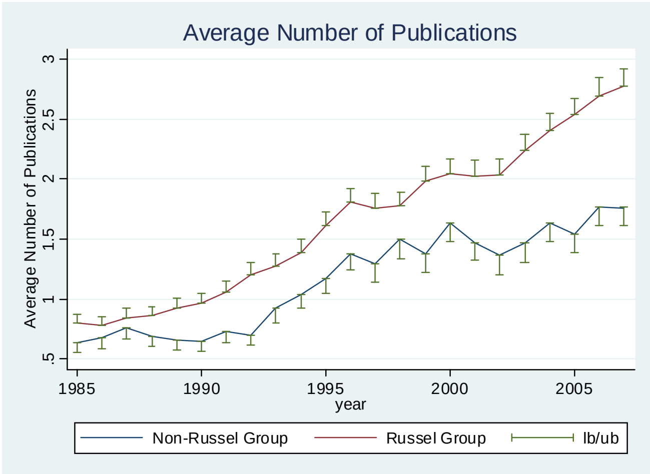

Figure 1: Average number of publications per faculty member.

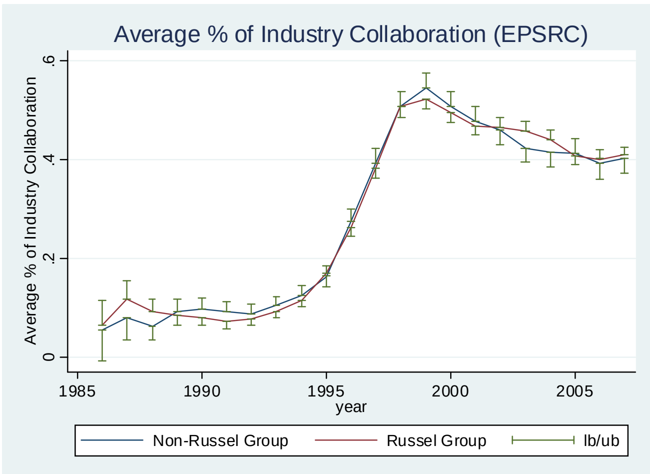

Figure 2: Average percentage degree of industry collaboration based on EPSRC funds.

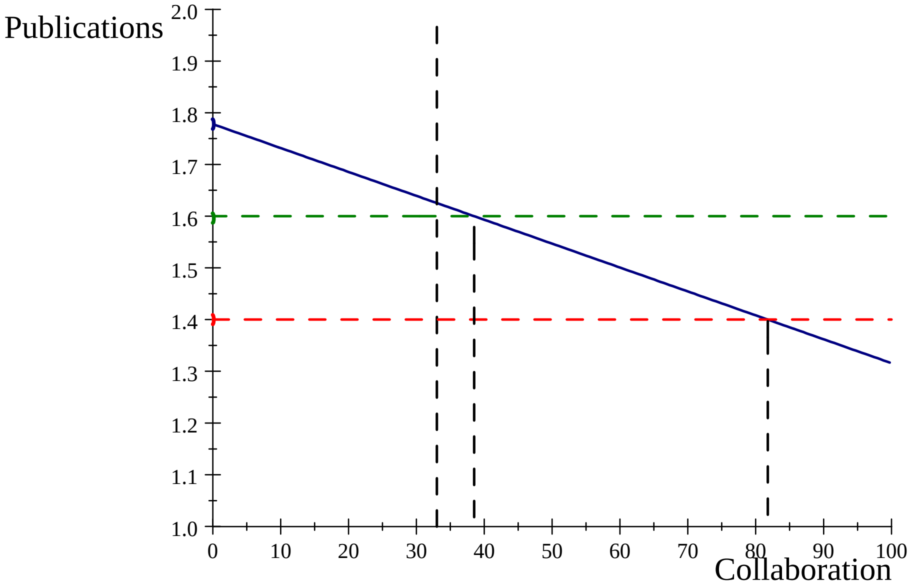

Figure 3: Predicted number of publications for any degree of industry collaboration.

Table 1: List of Universities

Russel Group Universities	Number of ID	Number of Observations
Birmingham, University of	204	2467
Bristol University	87	988
Cambridge, University of	200	2433
Cardiff, University of	110	1310
Edinburgh, University of	99	1184
Glasgow, University of	109	1543
Imperial College London	294	3495
Kings College London	55	587
Leeds, University of	179	2060
Liverpool, University of	110	1401
Manchester, University of	242	1454
Newcastle, University of	155	1956
Nottingham, University of	176	2118
Oxford, University of	103	1271
Queens University, Belfast	107	1453
Sheffield, University of	185	2110
Southampton, University of	145	1734
University College London	137	1699
Warwick, University of	72	960
Other Universities		
Aberdeen, University of	49	591
Aston University	64	897
Bangor University	32	328
Brunel University	87	988
City University, London	68	892
Dundee, University of	57	700
Durham, University of	49	528
Essex, University of	30	435
Exeter, University of	44	509
Hull, University of	41	533
Heriot Watt University	153	1838
Lancaster, University of	27	344
Leicester, University of	40	421
Loughborough, University of	247	3033
Queen Mary London	90	999
Reading, University of	51	656
Salford, University of	109	1362
Strathclyde, University of	201	2532
Swansea University	97	1299
UMIST (merged with Machester in 2004)	224	2804
York, University of	31	356

* Researchers can belong to more than one university during their career. Therefore the numbers of id do not add up to 4066.

Table 2: Descriptive Statistics

Variable	Non-Russel Group				Russel Group				Comparison
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean Diff. (Non-Russel - Russel)
Dependent Variables									
Number of publications	1.07	2.10	0	41	1.57	2.56	0	37	0.497 (0.021)***
Number of co-author weighted publications	0.41	0.76	0	11.58	0.59	0.92	0	12.27	0.171 (0.007)***
Number of Impact Factor weighted publications	0.89	2.64	0	69.59	1.52	3.85	0	73.96	0.624 (0.029)***
Number of citation weighted publications	9.42	33.01	0	1747	16.59	49.78	0	2445	7.175 (0.379)***
Number of applied technological publications (Level 1)	0.18	0.56	0	11	0.25	0.69	0	12	0.073 (0.006)***
Number of basic technological publications (Level 2)	0.41	1.07	0	17	0.62	1.37	0	24	0.203 (0.011)***
Number of applied scientific publications (Level 3)	0.22	0.95	0	22	0.34	1.23	0	26	0.118 (0.010)***
Number of basic scientific publications (Level 4)	0.06	0.41	0	17	0.12	0.59	0	15	0.062 (0.005)***
Explanatory Variables									
EPSRC funds in £1000	60.1	163.9	0	7569	78.7	225.8	0	11400	18.591 (1.762)***
Fraction of EPSRC funds with industry collaboration	29.9%	38.7%	0.0%	100.0%	31.1%	38.3%	0.0%	100.0%	0.012 (0.004)***
Fraction of 5 year accumulated EPSRC funds with industry collaboration	23.4%	33.4%	0.0%	100.0%	24.6%	33.2%	0.0%	100.0%	0.012 (0.004)***
Number of patents	0.30	0.23	0	11	0.04	0.27	0	9	0.014 (0.002)***

The total number of observations for Russel Group is 42091 (3431 academics); for Non-Russel Group it is 28066 (2269 academics).

Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Inactive Staff -or those having no publications and no EPSRC funds- are excluded

Table 3: Regressions of the number of publications on industry collaboration

	(1) GLS Fixed effects	(2) GMM Instrumenting for publications and rank	(3) GMM Instrumenting for publications, rank and industry collaboration	(4) GMM Instrumenting for the full set (benchmark)
Constant	0.453***	0.357***	0.312***	0.308***
	[0.0153]	[0.0412]	[0.0476]	[0.0453]
Lagged Dependent Variable				
Ln (publications)$_{t-1}$		0.0918	0.0195	0.0419
		[0.0900]	[0.0798]	[0.0709]
Ln (publications)$_{t-2}$		0.0510***	0.0480***	0.0495***
		[0.0115]	[0.0118]	[0.0115]
Collaborative Research				
Had some funding$_{t-1}$	0.0309**	0.0170	0.174**	0.135**
	[0.0126]	[0.0208]	[0.0701]	[0.0640]
Had some funding with Industry$_{t-1}$	0.0412***	-0.00804	0.130*	0.108*
	[0.0157]	[0.0231]	[0.0664]	[0.0625]
Ln (fraction of acumulated funding with Industry)$_{t-1}$	0.00319	-0.0115	-0.301**	-0.266**
	[0.0350]	[0.0492]	[0.132]	[0.126]
Patents Filed				
# Patents $_{t}$	0.0262**	-0.0545	-0.105*	0.0516
	[0.0120]	[0.0676]	[0.0608]	[0.0470]
# Patents $_{t-1}$	0.00996	-0.160	-0.261**	-0.0359
	[0.0128]	[0.140]	[0.126]	[0.0477]
# Patents $_{t-2}$	0.0237*	-0.0857	-0.149	0.0394
	[0.0137]	[0.170]	[0.158]	[0.0549]
Academic Rank				
Senior Lecturer$_{t-1}$	0.0724***	0.226***	0.198***	0.194***
	[0.0154]	[0.0489]	[0.0479]	[0.0456]
Reader$_{t-1}$	0.149***	0.321***	0.296***	0.316***
	[0.0234]	[0.0727]	[0.0742]	[0.0711]
Professor$_{t-1}$	0.184***	0.216***	0.174**	0.140*
	[0.0267]	[0.0708]	[0.0763]	[0.0718]
Controlled by Years	Yes	Yes	Yes	Yes
Number of observations	34086	34086	34086	34086
Number of ids	4066	4066	4066	4066
R^2	0.020			
Number of Instruments		198	297	347
AR(1) test z (p-value)		0.0000	0.0000	0.0000
AR(2) test z (p-value)		0.8853	0.3366	0.4706
Sargan test p-value		0.0616	0.1851	0.2754

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regressions of the number of publications on industry collaboration with interactions

	(1) GMM - Interaction with Russell Group		(2) GMM - Interaction with Stars		(3) GMM - Interaction with Seniors	
	Russell Group Effect	Non Russell Group	Stars Effect	Non Stars	Seniors Effect	Juniors
Constant	0.313***		0.265***		0.313***	
	[0.0444]		[0.0721]		[0.0468]	
Lagged Dependent Variable						
Ln (publications)$_{t-1}$	0.0204		0.0648		0.061	
	[0.0600]		[0.0595]		[0.0710]	
Ln (publications)$_{t-2}$	0.0532***		0.0544***		0.0589***	
	[0.0116]		[0.0117]		[0.0119]	
Collaborative Research						
Had some funding$_{t-1}$	0.129*	0.0243	0.404	-0.297	0.390***	-0.193**
	[0.0733]	[0.0791]	[0.405]	[0.419]	[0.0910]	[0.0757]
Had some funding with Industry$_{t-1}$	0.119*	0.00471	0.190**	-0.087	0.163*	-0.0176
	[0.0718]	[0.111]	[0.0904]	[0.108]	[0.0951]	[0.132]
Ln (fraction of acumulated funding with Industry)$_{t-1}$	-0.253*	-0.063	-0.660***	0.476**	-0.729***	0.637**
	[0.145]	[0.212]	[0.215]	[0.235]	[0.194]	[0.262]
Patents Filed						
# Patents $_{t}$	-0.0534	0.0687	0.0592	-0.226*	0.0521	0.0384
	[0.105]	[0.111]	[0.0381]	[0.137]	[0.0570]	[0.101]
# Patents $_{t-1}$	-0.201*	0.161	0.024	-0.0967	-0.00913	-0.0112
	[0.108]	[0.110]	[0.0342]	[0.127]	[0.0609]	[0.0911]
# Patents $_{t-2}$	-0.0128	0.061	-0.0598*	-0.0996	0.102	-0.023
	[0.110]	[0.117]	[0.0307]	[0.139]	[0.0956]	[0.118]
Academic Rank						
Senior Lecturer$_{t-1}$	0.198***		0.171***			
	[0.0455]		[0.0433]			
Reader$_{t-1}$	0.310***		0.229***			
	[0.0703]		[0.0683]			
Professor$_{t-1}$	0.160**		0.148**			
	[0.0702]		[0.0676]			
Controlled by Years	Yes		Yes		Yes	
Number of observations	34086		34086		34086	
Number of ids	4066		4066		4066	
Number of Instruments	501		500		347	
AR(1) test z (p-value)	0.0000		0.0000		0.0000	
AR(2) test z (p-value)	0.1886		0.4881		0.4620	
Sargan test p-value	0.5517		0.3924		0.3169	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regressions of the weighted number of publications

	(1) GMM publications weighted by number of coauthors	(2) GMM publications weighted by journal impact factor
Constant	0.200***	0.174***
	[0.0285]	[0.0360]
Lagged Dependent Variable		
Dependent Variable$_{t-1}$	0.00679	0.0838
	[0.0727]	[0.0727]
Dependent Variable$_{t-2}$	0.0550***	0.0569***
	[0.0114]	[0.0145]
Collaborative Research		
Had some funding$_{t-1}$	0.0567	0.131**
	[0.0393]	[0.0593]
Had some funding with Industry$_{t-1}$	0.0489	0.103*
	[0.0388]	[0.0559]
Ln (fraction of acumulated funding with Industry)$_{t-1}$	-0.166**	-0.115
	[0.0774]	[0.115]
Patents Filed		
# Patents $_{t}$	0.0161	0.00443
	[0.0391]	[0.0603]
# Patents $_{t-1}$	-0.032	-0.0238
	[0.0409]	[0.0537]
# Patents $_{t-2}$	0.029	0.066
	[0.0376]	[0.0566]
Academic Rank		
Senior Lecturer$_{t-1}$	0.0867***	0.162***
	[0.0263]	[0.0388]
Reader$_{t-1}$	0.191***	0.256***
	[0.0446]	[0.0639]
Professor$_{t-1}$	0.0266	0.248***
	[0.0429]	[0.0678]
Controlled by Years	Yes	Yes
Number of observations	34086	34086
Number of ids	4066	4066
Number of Instruments	348	366
AR(1) test z (p-value)	0.0000	0.0000
AR(2) test z (p-value)	0.1821	0.7342
Sargan test p-value	0.1273	0.2028

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regressions of the number of publications in each category

	(1) GMM Applied technology	(2) GMM Basic technology	(3) GMM Applied science	(4) GMM Basic science
Constant	0.0563	0.0608	0.0579	0.0712*
	[0.0712]	[0.0919]	[0.0578]	[0.0423]
Lagged Dependent Variable				
Dependent Variable$_{t-1}$	0.0588***	0.123***	0.0873**	0.0601
	[0.0215]	[0.0234]	[0.0339]	[0.0436]
Dependent Variable$_{t-2}$	0.0014	0.0554***	0.0691***	0.0571**
	[0.0178]	[0.0175]	[0.0250]	[0.0286]
Collaborative Research				
Had some funding$_{t-1}$	0.0547	0.159**	0.0344	-0.0347
	[0.0558]	[0.0709]	[0.0523]	[0.0370]
Had some funding with Industry$_{t-1}$	0.115**	0.0279	0.0261	0.0151
	[0.0502]	[0.0634]	[0.0454]	[0.0286]
Ln (fraction of acumulated funding with Industry)$_{t-1}$	-0.151*	-0.108	-0.132**	-0.0983**
	[0.0790]	[0.0975]	[0.0662]	[0.0436]
Patents Filed				
# Patents $_t$	0.0671	-0.289**	-0.0106	0.065
	[0.0706]	[0.124]	[0.0895]	[0.0539]
# Patents $_{t-1}$	0.00334	0.0329	-0.0284**	-0.00239
	[0.0101]	[0.0270]	[0.0130]	[0.0134]
# Patents $_{t-2}$	-0.00332	0.00904	-0.0293	-0.000169
	[0.0314]	[0.0617]	[0.0479]	[0.0508]
Academic Rank				
Senior Lecturer$_{t-1}$	0.0528	0.136***	0.0891***	0.00728
	[0.0374]	[0.0477]	[0.0295]	[0.0200]
Reader$_{t-1}$	0.00248	0.222**	0.0966*	0.0666*
	[0.0692]	[0.0952]	[0.0552]	[0.0363]
Professor$_{t-1}$	-0.000987	0.134	0.0759	0.0415
	[0.0880]	[0.115]	[0.0554]	[0.0346]
Controlled by Years	Yes	Yes	Yes	Yes
Number of observations	14695	14695	14695	14695
Number of ids	3187	3187	3187	3187
Number of Instruments	104	104	104	104
AR(1) test z (p-value)	0.0000	0.0000	0.0000	0.0000
AR(2) test z (p-value)	0.7846	0.6441	0.7365	0.3960
Sargan test p-value	0.7576	0.5284	0.7824	0.2926

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1