The Impact of Industry Collaboration on Academic Research Output: A Dynamic Panel Data Analysis*

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Abstract

This paper studies the impact of university-industry research collaborations on academic research output, in terms of productivity, quality and direction of research. We report findings from a longitudinal dataset on researchers from 40 engineering departments in the UK between 1985 until 2007. Our results indicate that researchers with industrial links publish significantly more than their peers. Academic productivity, though, is higher for low levels of industry involvement as compared to high levels. However, most of this takes place at the expense of basic research.

Keywords: University-industry relationships, basic vs. applied research.

JEL codes: O3, L31, I23

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1 Introduction

In a modern economy it is essential to transform scientific research into competitive advantages. In the US, collaboration between universities and industry and the ensuing transfer of scientific knowledge has been viewed as one of the main contributors to 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), one of the main factors for the poor commercial and technological performance of the EU in high-tech sectors.

Increasing the transfer of knowledge from universities to industry is a primary policy aim in many 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 thirty 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 the industry have been found to have controversial side effects on the production of scientific research itself (see e.g. Geuna and Nesta 2007). Florida and Cohen (1999) argue that industry collaboration might come at the expense of research, or at least of basic research; growing ties with the industry might be affecting the choice of research projects, "skewing" academic research

[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 emmanating 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 (SET), which set out a strategy to improve welfare by exploiting the UK strenghts in science and engineering.

from a basic towards an applied approach. Nelson (2001) also asserts that industrial involvement might delay or suppress scientific publication and dissemination of preliminary results, endangering the "intellectual commons" and the practices of "open science" (Dasgupta and David, 1994). 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).[3]

These claims bring forward three distinct questions for empirical research. (1) Does collaboration with the industry affect researchers' publication rates? (2) Does collaboration with the industry shift the focus away from basic research? (3) Does patenting delay or hinder publication? Previous research has investigated these questions mainly by focusing on patents and licensing and the formation of start-up companies as knowledge transfer mechanisms (see Geuna and Nesta (2006) and Baldini et al. (2008) for recent reviews). Several papers, however, have stressed the relatively small role of the commercialisation of intellectual property rights relative to other channels of knowledge transfer. According to the firms, collaborative links through joint research, consulting or training arrangements are reported to be far more important transmission channels than patents, licenses and spin-offs (Cohen et al. 2002). Contract research or joint research agreements are also more important than patenting according to the academics (Agrawal and Henderson, 2002), and as a result, more widespread (D'Este and Patel, 2007), especially in Europe (Geuna and Nesta, 2006). Unfortunately, possibly because of lack of comparable data, we know very little about the impact of collaborative research agreements on scientific research.

The main objective of this paper is to study the impact of university-industry research collaboration on academic research output. We compiled a unique, longitudinal dataset containing academic research output (publications), public research funds (collaborative

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

and non-collaborative) and patents for all researchers employed in the Engineering departments of forty major universities in the UK between 1985 and 2007. Thus, we do not focus on a special type of researcher, but take into account (almost) the whole population of academic engineers in the UK. Moreover, by following academics over time, we are able to control for individual characteristics and estimate the relationship between industry collaboration and research output, taking into account potential reverse causality problems. And last but not least, our panel also allows us to take into account the dynamic aspect of publications.[4]

As a first contribution, we estimate the impact of collaborative research on academic output in terms of productivity, and direction of research. Our results on research productivity uncover the presence of two countervailing effects. Firstly, we find that the *presence* of industrial partners can be associated with a higher degree of academic research output; but then academic productivity decreases with the *intensity* of industry collaboration. As a result, researchers with a small but positive degree of industry collaboration are those with the highest predicted research output. Still, 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 slightly higher levels of collaboration, the predicted amount of publications would be lower. For researchers with very high levels of collaboration, the predicted value would be even lower than those with no funding at all.

By establishing a causal relationship between collaborative research and academic output, our dynamic panel results bolster empirical evidence from previous survey and cross-sectional studies. Survey studies on research collaborations suggest that industry involvement is linked to higher academic productivity (e.g. Blumenthal et al., 1986, and Gulbrandsen and Smeby, 2002). Though, 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". After controlling for endogeneity, we still find supportive evidence for the positive impact of the presence

[4] As shown by Arora et al. (1974) (among others), the peer-review system is informed by researchers' reputation and therefore past research performance strongly influence current performance.

of industry involvement on research output. The negative effect of collaboration intensity is also consistent with other survey results (Blumenthal et al., 1996) and cross-section empirical evidence (Manjarrés et al., 2008, 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.[5]

Our results on the direction of research show that, consistent with the "skewing" effect, industry collaboration has a negative effect on the more basic set of articles while it increases the most applied type of publications. Though a large number of works emphasized that industrial involvement might affect the direction of research and shift focus away from basic science, there is no empirical evidence supporting this. Our findings represent the first contribution confirming a "skewing problem" as suggested by survey studies, but stand out against empirical results. Blumenthal et al. (1986) and Gulbrandsen and Smeby (2002), using questionnaire data, find that academics whose research is supported by industry, report their choice of a research topic affected by its commercial potential. In contrast, empirical papers considering patenting and licensing as measures of industry involvement find a positive effect of patenting on the number of publications (Thursby and Thursby, 2007; Breschi et al., 2008) or no systematic link at all (Calderini et al. 2009; van Looy et al., 2006).

As mentioned above patenting represents the by far most studied channel of knowledge transfer that received particular attention not only by scholars but by policy makers as well. We can therefore not ignore it when talking about involvement with industry, and hence, as a second contribution, we compare and separate out the effects of collaboration via research grants from those of patenting. We find, once controlling for the dynamic effect of publications and research partnerships, that patenting does not hinder or delay the publication of research results, but does not enhance them either. These findings diverge from most recent empirical studies that suggest a positive effect of patenting

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

on publication rates (Azoulay et al., 2007; Stephan et al., 2007; Breschi et al., 2005; Buenstorf, 2006; van Looy et al., 2005; Calderini et al. 2009).[6] 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.

The paper is organized 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, and section 4 finally discusses and concludes.

2 Empirical strategy

2.1 Data

We have created a 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 the list of all universities with Engineering departments in the UK, we discarded those for which the academic calendars were available for less than five years.[7] Our final sample contains 40 major universities, including all the 19 universities part of the prestigious Russell group, a coalition of large, research intensive UK universities, as well as 21 smaller comprehensive universities and technological universities.[8] We concentrate on the engineering sector, as it has traditionally been associated with indus-

[6] 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. (2008) 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.

[7] 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 sublemented 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.

[8] Unfortunately, due to lack of sufficient data, we were not able to include any of the so called "new", post-1992 universities into our sample.

try collaboration and it contributes substantially to industrial R&D (Cohen et al. 2002). We recognize though that engineering differs substantially from other fields, especially in its highly fragmented character. Thus, we include all the Engineering departments of the selected universities.

We retrieved names and academic ranks of university researchers from university calendars. We thereby solely focussed on academic staff carrying out both teaching and research and did not consider research officers or teaching assistants. Where possible we recorded full names, but at least last names with two initials. We followed the researchers' career paths between the different universities in our dataset.[9] Academics leave (and join) our dataset at different stages in their career, when they move to (from) abroad, the industry, departments other than engineering (e.g. chemistry, physics, computer science), or universities not part of our dataset. In total we collected 7707 individuals, 5172 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, patents and research funds.

Publications. Data on publications was derived from the ISI Science Citation Index (SCI). Publications in peer-reviewed journals are not the only measure for research output, but the best recorded and the most accepted one, as publications are essential in gaining scientific reputation and for career advancements. We collected information on all the articles published by the researchers in our database while they were employed at one of the institutions in our sample. Most entries in the SCI database include detailed address data that allow us to identify institutional affiliations and unequivocally assign articles to individual researchers.[10] The same data includes addresses of coauthoring organisations and hence provides information about collaboration partners.

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

[10] Articles without address data had to be ignored. However, we expect these missing information to be systematical and hence time dummies to efficiently control for the effects in our regression analysis.

Research funds. The research projects considered in this analysis were 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. Data on these grants is available from 1986 onwards. Driven by recent policy developments it encourages commercial and collaborative research and as a result since 1995 around 40% of grants have involved partners from the industry. In comparison, before 1995 this figure was only 15%. These funds of course are mediated by the research council and can hence not be taken as a proxy for direct funds from the industry. Nevertheless, since the EPSRC is by far the largest provider of funds for research in engineering they allow a very comprehensive and comparable insight into the dynamics of university-industry-collaborations. The database contains information on start year and duration of the grant, total amount of funding, names of principle and coinvestigators, institution of the principle investigators (grant receiving institution) and names of partner organisations.

Patents. Next, we obtained patent data from the European Patent Office (EPO) database. We collected those patents that identify the aforementioned researchers as inventors and have been filed while they were employed at one of the institutions. Thereby, we did not only consider patents filed by the universities themselves but also those assigned to third parties, e.g. industry or governmental bodies. The filing date was chosen as it represents the closest date to invention. As the filing process can take several years, we were only able to include patents awarded until 2007, hence filed before 2005.[11]

Sample. Since information on patents and grants was not available for all the years we had to reduce our sample to the period 1986 to 2004. We further exclude all inactive researchers (those that have no publications, patents or funds during the entire sample

[11] 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 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 is therfore necessary to compare priority numbers to ensure that each invention is only included once in our data.

period) leaving us with our final sample of 4066 individuals with 44722 year observations, 75380 publications, 29347 research projects and 1828 patents.

2.2 Variables and Descriptive Statistics

In this section we explain the variables we have used to estimate our models. To do so, we have created measures of research output, research collaboration, patents, and time variant and time invariant control variables.

Research output. We created two variables as proxies for the quantity of research produced in a given year: (1) the normal count of publications (the number of publications for which the researcher is an author); and, (2) the "coauthor-weighted" count of publications (fractional count of publications for which the researcher is an author, with the weights being the inverse of the number of coauthors).[12] The second measure might be preferable because it avoids double counting of publications (see e.g. Hanish et al., 1998; Defazio et al. 2008).

To adjust research productivity by its relative quality, we use an additional proxy: (3) the "impact-factor-weighted" sum of publications in a given year, with the weights being the impact attributed to the journal in which the publication appears. We use the ISI Impact Factor, a measure of importance attribution based on the number of citations the journals receive. Though it is not a direct measure for the quality of a particular article, it represents the importance attributed to it by peer review. As the impact of journals differs between years and journals are constantly added to the SCI or change names, we collected journal impact factors for all the years 1985 to 2007, to capture all SCI journals and to allow for variation. As an alternative measure for quality we additionally use a forth proxy: (4) the average yearly number of citations an article received in SCI journals until 2008. Though citation levels can differ across subjects and depending on

[12] Mathematically, 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.

the time-lag, this is taken care of by controlling for individual effects and by including year dummies into our regressions. Citations should hence present a reliable measure for importance attributed to academics' work by their peers.

Figure 1 shows that the average number of publications per staff has been rising continuously over the survey period, in both the elite and the non-elite groups of universities.[13] Table 2 shows the all-time averages and the differences between the two groups of universities. Consistent with Figure 1, 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). Also, after taking into account the number of coauthors these differences stay significant (0.61 vs. 0.42). Once we adjust for quality, the differences are even larger (1.77 vs. 0.97).

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. Basic scientific research (level 4) only represents 7% of the articles in our sample which is given the applied character of engineering science. Thus Godin (1996) and van Looy et al. (2006) interpreted the four categories as papers concerning science (levels 3 and 4) and those relating to technology (levels 1 and 2). They then differ between (1) applied technology, (2) basic technology, (3) applied science and (4) basic science. Accordingly in our sample categories 1 and 2 are prevalent representing 27% and 46% of all publications. Only 27% of articles have been published in science oriented journals. To examine these differences in detail we will analyse all four categories separately.

[13]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.

Collaborative research and patents. We divide the total monetary value from the research grants among the principal investigator (PI) and coinvestigator(s). Although we include coinvestigators as beneficiaries, we did positively discriminate PI's by assigning them half of the grant value and splitting the remaining 50% amongst their coinvestigators. We spread the grant value over the whole award period. If the grant is 2 years we split it equally, if it is over 3 or more years, the first and last years (which are assumed not represent full calendar years) receive half shares and it is otherwise split equally.[14] 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 start of the project.

Each award holds information on research partners, and grants with one or more partner from the industry were considered as "collaborative grants". Since our objective is to evaluate not only the influence of the existence of industry partnerships but also the intensity of collaboration activity, we also compute the fraction of funds with one or more partners from the industry over all EPSRC funds. We use a 5-year stock of 'accumulated' collaboration because it should capture better the true profile of the academic. We also constructed two time-variant dummy variables, which allow for a differential effect for those researchers with no funding at all, for those with some funding but no collaboration, and for those with funding with industrial partners in the 5 years preceeding the publication.

Figure 2 reports the percentage of industry involvement through EPSRC funds shows that with regard to industry collaboration the two groups of universities do not seem to differ much. Nevertheless, Table 2 reveals that these differences no matter how small are still significant and on average the percentage of the Russel group is slightly higher (33% vs. 31%). The trend for a sudden increase in industry collaboration through EPSRC funding in the late 1990's seems to have affected all UK universities equally as does the stagnation in recent years. This might imply severe changes in funding allocation through

[14] Mathematically, if $Fund_{i,s,d,f}$ is the monetary value of a grant f received by researcher i in year s (start year) and duration d, the value of the grant assigned to a year t is $Fund_{i,s,d,f}$ for $t = s$ if $d = 1$; $(Fund_{i,s,d,f})/2$ for $t = s$ and $t = s + 1$ if $d = 2$; and $(Fund_{i,s,d,f})/(2(d-1))$ for $t = s$ and $t = s + d - 1$ and $(Fund_{i,s,d,f})/(d-1)$ for $s < t < s + d - 1$ if $d > 2$.

the UK research councils. Table 2 shows, however, that the average EPSRC funding value is, as the number of publications, substantially higher for the prestigious Russell group of universities.

As mentioned above, we plan to separate out the effects of patents and funding partnerships. To measure the impact of academic patenting on the timing of the release of publications, we use the number of patents filed during the present and the 2 years preceding the publication. As we can see in Table 2, the average number of patents does also differ significantly between the two groups of universities (0.04 vs. 0.03). These values are very small for both groups, however, looking at the time trend we see that 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 them, however, do not vary at all over time and therefore cannot explain the dynamic variation, which is the focus of the paper. *Academic rank* is the only time-variant, noncollinear and hence most relevant demographic variable for our analysis. We therefore integrate information on the evolution of the researchers' academic status from lecturer to senior lecturer, reader and professor into our analysis. *Year* dummies were included in all regressions to control for time effects in our panel.

Interaction Variables. The effect of industry collaboration on research output might differ for different types of individuals. Therefore, in some models, we interact our measure of industry collaboration with several categories of individuals. First, since the descriptive statistics above show significant differences between different types of universities, we consider membership to the *Russell Group* as a category to interact with industry collaboration.

Second, there have also been several papers arguing that the most able researchers, which we call *stars*, may differ considerably from the rest of the academia in that they have plenty of opportunities to conduct their research and do not need to adjust to specific societal needs (e.g. Goldfarb, 2008). We define as stars all those researchers that are on the top 25 percentile of research productivity, with an average of 2 or more articles per year.

Third, senior staff members are more experienced and have larger networks to find research partners and hence the impact of industry partnerships on the publication behaviour of experienced staff might differ from that of less experienced members of staff, that might be less independent. We therefore create a variable that determines whether the researcher is at the start of her career (lecturer or senior lecturer) or she is at a later stage (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 reputation and status. We assume that her reputation and status depend on the stream of academic research output (in particular past and present publications in peer-reviewed journals), on the amount of research grants she generates (with and without the industry), and, on her commercial output (e.g. number of patents). The optimal time allocation problem consists in choosing the utility maximizing fraction of time she devotes to research; to collaborate with the industry; and to teach and perform all other tasks. The first order conditions involve first derivatives of the utility function with respect to the time devoted to research and collaborate with the industry. Thus, for any utility function which is not linear in publications, the first order conditions define an implicit function that expresses publications as a function of the relative time dedicated to collaborate with the industry. This function will be of course conditional to time-variant and invariant socio-demographic characteristics of the academic, and past publications.

Thus, to estimate how collaboration with the industry affects research output, we estimate a dynamic model where current realizations of the dependent variable are influenced not only by collaboration with the industry but also by past publications. Some of these regressors (industry collaboration, patents, past publications and academic rank) are endogenous. Publishing, being a professor or getting many industrial funds, for example, are correlated with having a high cognitive ability, which is unobserved. 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. Accordingly, we formulate our reduced form equations as

$$\ln y_{it} = \beta_1 \ln y_{i,t-1} + \beta_2 \ln y_{i,t-2} + \beta_3 ic_{it} + \beta_4 p_{it} + \alpha x'_{it} + \mu_i + v_{it}$$

where y_{it} represents the research output variable, $y_{i,t-1}$ and $y_{i,t-2}$ are past realisations of the dependent variable, ic_{it} is a variable measuring the time spent collaborating with the industry, p_{it} is a variable measuring the time spent developing patents, and x_{it} is a vector time-variant explanatory variables. The error term contains two sources of error: the academic $i's$ fixed effect term μ_i, and a disturbance term v_{it}. 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. We treat the lagged number of publications, the number of patens, 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 their differences instrumented. Finally, we use department size as additional exogenous instrument.

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

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 the results change 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, the industry collaboration terms are instrumented as endogeneous variables while patents are still considered exogenous. Finally, in the fourth model, which we consider 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. The Arellano-Bond tests do not reject the null that there is absence of second (or higher) order correlation of the disturbance terms of our specifications, required for consistency of our estimates. The Sargan/Hansen tests are also insignificant suggesting that the models do not suffer from over-identification.

In all specifications, the exponent of the estimate of the constant term can be considered as "baseline" productivity prediction, i.e. the expected number of publications for a researcher who does not have any funding, or patents and is at the start of her career (lecturer - lowest tenured academic rank, the omitted category). The baseline prediction for the number of publications ranges from 1.57 articles per year in the GLS specification to 1.36 in the last GMM model. In the GMM specifications part of the effect of the constant is taken up by the previous two years' publications.

The 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. In all specifications, the coefficients associated with the lagged publications are positive and, although the first lag is insignificant, the second lag is highly significant throughout. A publication two years prior increases the average number of current publications by at least 5%.

As expected, having received funding in the past five years enhances research productivity in all four specifications. In the GLS specification the coefficient is significant and equals 0.031, indicating that if a researcher receives funding she published, on average, 3% more articles than if she did not receive any funding. More importantly, if some of this funding involves a partner from the industry the average number of publications increases by a further 4%. As a result, in the latter case our academic would publish 7% more articles than without any funding. Further, the effect of the intensity of a researcher's involvement in collaborative research is also positive albeit insignificant.

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 specification), funding does not have any significant impact on the number of publications. However, as soon as we take into consideration that funding is endogenous (columns three and four), the collaboration variables become significant. Interestingly, receiving grants that involve a partner from the industry has a positive effect but the coefficient associated to the fraction of funding grants involving industry partners is negative.

In the last -benchmark- specification, an academic without funding is predicted to publish 1.4 articles per year. If she obtained non-industrial funding she would obtain 14% more (1.6 publications), and an additional 11% (1.78 publications), that is 27%, if a marginal fraction of funding involved partners from the industry. However, as the level of collaboration increases, by say 1%, the predicted amount of publication decreases by

0.26%.

The predicted values for any level of collaboration are depicted in Figure 3. As we can see, for the average level of collaboration, 33%, the academic output is predicted to be higher than if the predicted value for no collaborative funding. For slightly higher levels of collaboration (more than 38.5%), the predicted amount of publications would be lower than if one only had non-industrial funding. For very high levels of collaboration (more than 81.8%), the predicted amount of publications would be lower than if one had no funding at all.

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). Significant are the current years observation and the second lag variable, each of which increase the number of articles by 2%. However, when we allow for the dynamic effect of the publications, the signs turn negative. If one assumes industry collaboration and patents exogenous the coefficients associated to patents are insignificant but become significant if collaboration is assumed endogenous. Finally, in our fourth and 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 allow for endogeneity.

We can again observe differences between the GLS and the GMM specifications with respect to the effect of the academic rank. In the GLS regression, higher stages in the academic career can be associated with more 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 the academic promotion process, which is undoubtedly linked to research output, we find evidence for reduced productivity over the career life-cycle

(Levin and Stephan, 1991)

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. In specification one we separate out the effects of academics that belong to the elite group of universities (Russell Group) from the academics at other universities. We then analyse independently the "Star" researchers, those that are in the top 25% percentile in terms of yearly publications, which in our sample is an average of 2 or more publications per year. We further in model 3 distinguish between the effects on senior academics (Readers and Professors) and junior academics (Lecturer and Senior Lecturer). 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 above while the second column (interaction effect) corresponds to the estimates for the comparison group.

Despite the dissimilatities in the descriptive statistics, the effect of industry collaboration on publication record does not seem to be very different for researchers at a Russell Group university. As can be observed from column one, estimates and levels of significance for the Russell Group academics do not differ very much from those in our benchmark model in column four of Table 3. An exception are 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% of the publications). Although statistically not significantly different, the effect of patents is more positive for academics at universities that are not a member of the Russell Group.

The second block of regressions presents the estimates for a differentiated effect of industry collaboration and patents for academics in the top 25 percentile in terms of average publication numbers. As in the previous regression, we observe that the estimates for "star" scientists are similar to the average estimated by the benchmark model. The magnitudes of the coefficients are similar as are the levels of significance. Academics not categorized as "stars" do not differ significantly in their estimates. 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 stronger than in the benchmark model and that they differs significantly from the coefficients for junior academics. 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 50% of the constant) as is collaboration with the industry (0.163 equivalent to a further 20%). 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 benefits 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, the four specifications model the number of publications weighted, respectively, by the number of coauthors, the impact factor of the journal where they are published, both the impact factor of the journal and the number of coauthors, and, the number of citations they received.

When weighting the number of publications by these factors, some of the effects of funding and collaboration become insignificant. Having received funding is only significant if one weights the publications by impact factor or by impact factor and number of coauthors. Having received funding that involves industrial partners has still a positive effect on the number of publications weighted by coauthors but it is not significant. Given that the intensity of collaboration has again a significant and negative effect, industry collaboration has an overall damaging effect on the coauthor weighted publication record.

Instead, if one weights the publications by the impact factor, the intercept associated with having some funding is positive and significant but the measure of intensity is insignificant. Therefore, collaborated with the industry is unambiguously positive for publications if they are weighted by the impact factor. Both effects are mixed in the third column and therefore the effect of collaboration with the industry is insignificant. The same happens if we weight the publications by the citations they receive.

Another remarkable result when weighting by the number of coauthors is that a Professor does no longer publish more than a Lecturer. Professors may publish with an increased number of coauthors, diluting the effect of seniority on publications. When looking at the publications weighted by impact factor, the effect of Professor becomes again positive and significant. Finally, in the fourth column, we show that being a Professor seems to have a significantly lower impact on the number of citations than being a Lecturer.

3.4 Basicness of Publications

Table 6 reports the estimates for the effect of industry collaboration on the basicness of research. We present four regression representing the four levels ranging from "applied technology" to "basic scientific". Column one shows that industry collaboration has a significant positive effect on the number of publications in "applied technology" journals. Here, funding alone does not increase the number of publications in "applied technology" unless it involves industrial partners. Although, as in the aggregate model, the number of publications in this category decreases with the intensity of collaboration, the effect is much weaker.

In all the other categories, industry collaboration is either insignificant or has a negative impact. For "engineering and technological science" (basic technology), the number of publications is positively affected by research funding grants. Industry funding on the other hand has no additional effect on research productivity. We can conclude that funding has a positive impact on technological research ("applied technology" and "engineering and technological science") but that only industry funding can be associated with publications in "applied technology" journals while only public funding is linked to "basic technology".

This positive effect of funding cannot be found for scientific research. For both, level 3 (applied scientific) and level 4 (basic scientific) funding does not have an effect per se but we instead observe decreasing numbers of publications for an increasing fraction of industry collaboration. A researcher publishes most in scientific research journals if she does not receive any research grants.

The release of patents has a negative effect on the number of publications in "engineering and technological science" (basic technology). As this represent the field of research most closely related to the invention of new technology and hence patenting activity the negative sign could indeed confirm the secrecy hypothesis. Past patents have a positive impact though they are not significant. Patenting in general also seems to have a negative effect on level 3 publications (applied scientific).

Interestingly, Professors do not publish more than Lecturers for any of the four categories. The number of publications in "applied technology" does not differ at all between the different academic ranks. As for the other 3 levels, Readers publish the most.

4 Discussion and conclusion

Our main results for this panel indicate that researchers benefit from collaborating with the industry. Researchers with no industrial involvement are predicted to publish less than those with a small degree of collaboration. Nevertheless, higher levels of industrial involvement affect negatively research productivity in terms of number of publications. Still, 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 slightly higher levels of collaboration, the predicted amount of publications turns out to be lower.

Our results also indicate that correcting for the reverse causality of industry collaboration and research output is crucial when trying to estimate the true impact the former on the latter. Since both number of papers and industry collaboration are positively affected by unobserved factors such as intelligence and/or ability, the impact of excessive diversion from academic activity through industrial collaboration can be seriously underestimated when not using an adequate estimation method.

In terms of policy prescription, our findings suggest that encouraging universities to collaborate moderately with the industry is a beneficial policy not only per se but also for academic productivity. But, discouraging high levels of industry collaboration is also advisable. At the same time, we find evidence of a skewing effect. 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.

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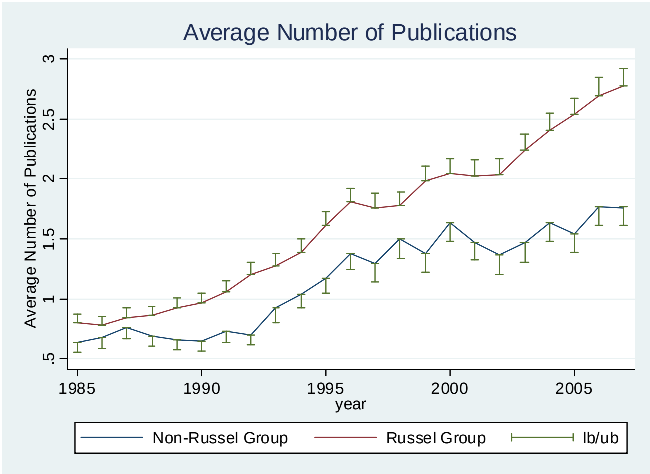

Figure 1: Average number of publications per faculty member.

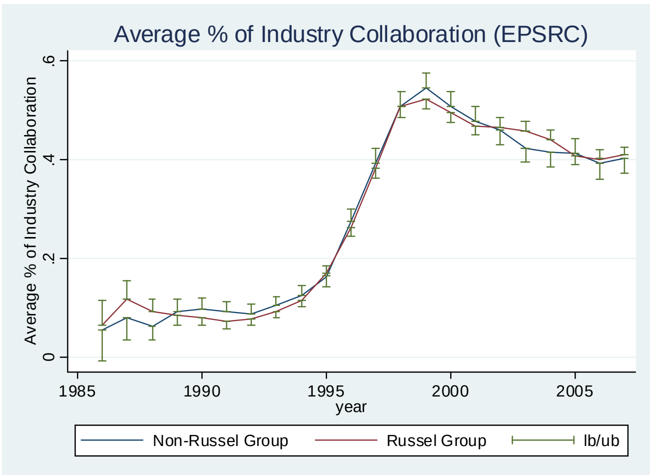

Figure 2: Average percentage degree of indstry collaboration based on EPSRC funds.

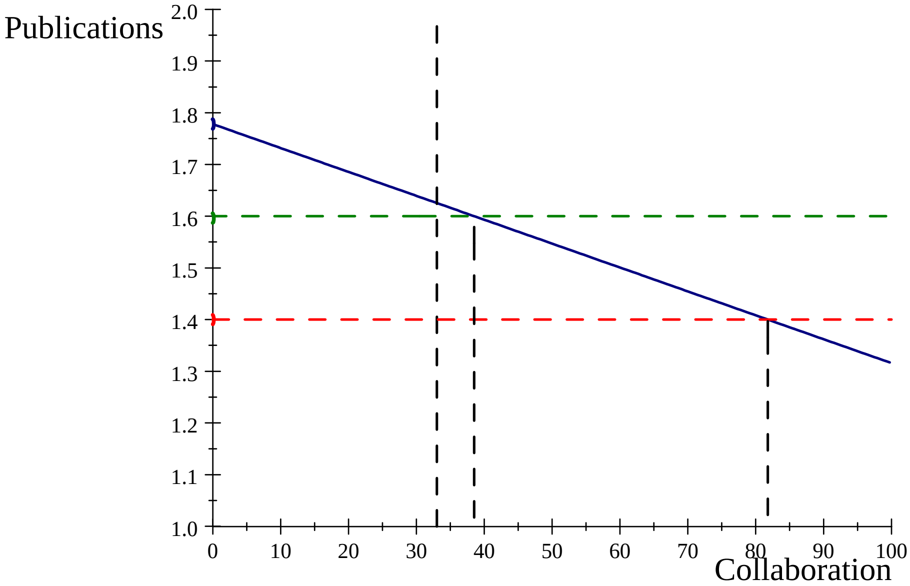

Figure 3: Predicted number of publications for any degree of industry collaboration.

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 Mean	Std.Dev.	Min	Max	Russel Group Mean	Std.Dev.	Min	Max	Comparison: 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

	GLS Fixed effects	GMM Instrumenting for publications and rank	GMM Instrumenting for publications, rank and industry collaboration	GMM Instrumenting for the full set
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

	GMM - Interaction with Russell Group		GMM - Interaction with Stars		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

	GMM publications weighted by number of coauthors	GMM publications weighted by journal impact factor	GMM publications weighted by citations
Constant	0.200***	0.174***	1.114***
	[0.0285]	[0.0360]	[0.110]
Lagged Dependent Variable			
Dependent Variable$_{t-1}$	0.00679	0.0838	0.0695
	[0.0727]	[0.0727]	[0.0732]
Dependent Variable$_{t-2}$	0.0550***	0.0569***	0.0502***
	[0.0114]	[0.0145]	[0.0119]
Collaborative Research			
Had some funding$_{t-1}$	0.0567	0.131**	-0.151
	[0.0393]	[0.0593]	[0.139]
Had some funding with Industry$_{t-1}$	0.0489	0.103*	0.00591
	[0.0388]	[0.0559]	[0.127]
Ln (fraction of acumulated funding with Industry)$_{t-1}$	-0.166**	-0.115	-0.405
	[0.0774]	[0.115]	[0.252]
Patents Filed			
# Patents $_{t}$	0.0161	0.00443	0.0797
	[0.0391]	[0.0603]	[0.150]
# Patents $_{t-1}$	-0.032	-0.0238	-0.159
	[0.0409]	[0.0537]	[0.138]
# Patents $_{t-2}$	0.029	0.066	-0.0392
	[0.0376]	[0.0566]	[0.123]
Academic Rank			
Senior Lecturer$_{t-1}$	0.0867***	0.162***	0.301***
	[0.0263]	[0.0388]	[0.0974]
Reader$_{t-1}$	0.191***	0.256***	0.357**
	[0.0446]	[0.0639]	[0.152]
Professor$_{t-1}$	0.0266	0.248***	-0.422***
	[0.0429]	[0.0678]	[0.147]
Controlled by Years	Yes	Yes	Yes
Number of observations	34086	34086	34086
Number of ids	4066	4066	4066
Number of Instruments	348	366	366
AR(1) test z (p-value)	0.0000	0.0000	0.0000
AR(2) test z (p-value)	0.1821	0.7342	0.5321
Sargan test p-value	0.1273	0.2028	0.0493

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

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

	GMM Lvl1	GMM Lvl2	GMM Lvl3	GMM Lvl4
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