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

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Abstract

The aim of this paper is to analyse the impact of university knowledge and technology transfer activities on academic research output. Specifically, we study whether researchers with collaborative links with the private sector publish less than their peers without such links, once controlling for other sources of heterogeneity. We report findings from a longitudinal dataset on researchers from two engineering departments in the UK between 1985 until 2006. 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.

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1　Introduction

Universities and other public research institutions have witnessed in the last two decades a push for greater industrial involvement and relevance in research (Tapper, 2007; Elton 1986). In the UK for instance, several policies in the 1990s directly aimed to favour research relevant to "Technological Foresight" (DES, 1991; Tapper 2007). Universities have also increasingly been encouraged to manage intellectual property (IP) to better exploit their research (HM Treasury and DTI, 1998; Lambert, 2003; Lockett and Wright, 2005). Since then university patents together with license agreements and revenues have increased dramatically.[1]

Many people have hailed the surge in university-industry collaboration and the increased number of patents and licenses as a great benefit to society (see e.g. UK National Audit Office, 2002). Industry collaboration facilitates the transfer of basic knowledge and accelerates the exploitation of new inventions. The financial benefits from contract research, patents (through licenses and royalties) and spin-off companies provide additional sources of funding, which can be, for example, allocated to new research areas.

Other sources from inside universities as well as from the government, however, have expressed concerns about the possible consequences of an increased emphasis on knowledge and technology transfer (see Geuna and Nesta, 2007, for a review). Florida and Cohen (1999) argue that industry collaboration and commercialisation 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 from a basic towards an applied approach. Nelkin (1984), among others, also alerts that the pressure for transfer technology and knowledge might endanger the "intellectual commons" and the practices of open science. Commercial development might delay or suppress scientific publication

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[1]The Annual Survey on University Technology Transfer Activities, for example, revealed that the top 125 institutions in the US and Canada disclosed 2,238 new inventions and issued 347 new patents in 2002-03, representing an increase of 19 and 59 percent respectively on the previous year. The total licensing income increased from £31.3m in 2003 to over £40m in 2004, with the number of licence agreements more than doubling during this period.

and dissemination of preliminary results.[2]

The first objective of this study is to analyse the impact of university-industry collaboration on research output in terms of productivity, quality and direction of research. We exploit a longitudinal database containing individual demographic characteristics, publications, research funds and patents for all the researchers employed in the last 20 years in the engineering departments of Imperial College London and City University of London. Specifically, we study whether researchers with links with the industry, via coauthorships or funding partnerships, publish more and more basic papers and in better journals than their peers without such links. Our longitudinal sample also allows us to control for observable and unobservable characteristics such as academic rank and cognitive ability and obtain unbiased and consistent estimators of the impact of industry collaboration on research output, taking into account potential reverse causality problems. With respect to the direction of research, we estimate whether industrial collaboration has any impact on the likelihood of publishing applied research.

Our second objective is to analyse further the relationship between patenting and publication of research results. Specifically, we analyse whether patenting hinders or delays publication of research outputs. Recent studies suggest instead that patenting has a positive effect on publication rates (Azoulay et al. 2008, Fabrizio and Di Minin, 2008). This can be attributed to the fact that the same research stream may lead to publications and yield patents or to the fact that the experience of patenting, licensing, and working with the licensee to transfer technology may also prompt additional research questions. Our dataset, which has information on industry collaboration and patents, should enable us to separate the potential complementarities between patenting and publishing from the effects of collaborating with the industry.

The limited existing evidence that attempt to uncover the relationship between industry collaboration and academic output offers mixed results. Goldfarb (2008) tracks a

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[2]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) and Nature (2007), have recently addressed the consequences of higher university-industry collaborations.

sample of 221 American university researchers funded by the NASA in 1981. Based on a follow-up of those in 1988, he concludes that researchers funded by the NASA experienced a reduction in academic output. Other survey studies, though, show that more industry links are associated with higher productivity. Gulbrandsen and Smeby (2002), for example, show that professors with industrial funding in Norway report more publications than their colleagues. Blumenthal et al. (1986), while confirming the positive implications of industry collaborations first, also points out that high levels of involvement can be associated with far lower levels of productivity. Larsen (2006), using data from a sample of the Technical University of Denmark and Manjarrés et al. (2007), analysing research activity at the University of Valencia, find a curvilinear, concave relationship between collaboration with industry and quantity of articles published.

Several survey studies seem to suggest that growing ties with the industry might be "skewing" academics research by inducing more 'applied research' papers as opposed to 'basic research' ones. Blumenthal et al. (1986) report that academics whose research is supported by industry are four times more likely to report that their choice of research topics has been affected by their commercial potential. In Gulbrandsen and Smeby (2002), researchers with funding from industry claim to perform significantly less basic research than researchers with no external funds or other types of external funds. On the other hand, Thursby et al. (2005) and Banal-Estanol and Macho-Stadler (2007) have argued that basic research might instead be reinforced by technology transfer objectives. Existing empirical evidence seems to indicate that the much-feared switch from basic to applied research might indeed not be occurring. Using academic staff data from six major universities, Thursby and Thursby (2007) find no systematic change in the proportion of publications in basic versus applied journals between 1983 and 1999. This corroborates the results by Hicks and Hamilton (1999), which indicated that the percentage of basic research that was performed at American universities remained unchanged between 1981 and 1995.

Despite the extensive interest in industry collaboration, most of the claims in either direction still lack satisfying empirical evidence stemming from the analysis of large and

longitudinal datasets. Most studies concentrate on small samples, making it difficult to infer the direction of causality between industry collaboration and research output, to control for unobservable characteristics such as cognitive ability and to draw comparisons across universities. Often, they also rely on questionnaire data or internal university information and therefore face problems in response rate and data reliability. This is especially the case for the UK where studies can be found only at an institutional level (e.g. Geuna, 1997) or are limited to questionnaire surveys with limited statistical evidence (e.g. Martinelli et al., 2007). As Geuna and Nesta (2006) claim, "there is an urgent need for more reliable and more useful data (on a time series basis) to be collected, not only on intellectual property activity but also on the inputs and outputs of the other activities carried out by researchers and research organisations."

Our results indicate that researchers with collaborative links with the private sector publish more than their peers without such links. Researchers who obtained only non-industrial funding or only coauthored papers with academic coauthors are likely to publish significantly less than their peers with a small fraction of industry collaboration. As the fraction of industrial collaboration increases, though, the number of publications decreases. High levels of industry collaboration end up being more negative in terms of research output than no collaboration at all. We also show that our results are robust if one takes into account the number of coauthors to avoid double counting of publications. Finally, we also show that the pattern is similar if one takes into account the impact of the journal in which the publications appear. Again, researchers that have highest predicted quality-weighted number of publications are those that have had a positive but minimal contact with the industry. With respect to the direction of their research, we find again a puzzling result: Both no collaboration with the industry or not having received any EP-SRC grant in the past decrease the likelihood of publishing applied research papers but at the same time, those that publish more applied papers are those who have a minimal fraction of their funding with industrial partners.

Our sample enables us to draw comparisons between different types of institutions since, despite sharing the same location, Imperial College and City University have a very

different profile. Whereas the former is one of the top ranked institutions in the UK and in the world in terms of research and technology transfer, the latter is a relatively small and new university. Despite these differences, the results for the two institutions are qualitatively the same.

In this paper we concentrate on the effects of collaborations between universities and private organisations, which is a particular form of knowledge and technology transfer. More progress has been made on the analysis of the impact of patenting, another form of technology transfer[3]. Agrawal and Henderson (2002) found that patenting did not affect publishing rates of 236 scientists in two MIT departments in a 15-year panel. Fabrizio and DiMinin (2005) identified a statistically positive effect of researchers' patent stocks on the publication counts in a sample of 166 academic patenters as compared to a matched set of non-patenting scientists. Stephan et al. (2007) also found that patenting and publishing relate positively. Azoulay et al. (2008) found 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. Studies by Ranga et al. (2003) and van Looy et al. (2006), which are based on data from the Katholik Universiteit van Leuven (KUL) in Belgium, did not find evidence for the skewing problem either, whereas Larsen (2006) reports that researchers with intermediate amounts of industry collaboration produce the most basic research.

Our paper suggests that the previous results are not only due to the fact that commercialisation activities provides involvement and feedback from the private sector. After controlling for the degree of industry collaboration and instrumenting for patents, we no longer find that patenting leads to an increase in the number of publications.

The paper is organized as follows: section 2 describes our empirical model and data; section 3 describes the results; and finally section 4 discusses and concludes.

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[3]See Baldini et al. (2008) for a recent review of the literature on the concerns stemming from university patenting and licensing activities. Geuna and Nesta (2006) surveys the effects of patenting activities in Europe.

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2 Empirical strategy

We exploit information from two universities based in London, UK, with a very different profile: Imperial College London, one of the top ranked institutions in the UK and in the world, and City University, a relatively small and a relatively new university that received the Royal Charter in 1966. The former was one of the co-founders of the University of London whereas City University formed out of a vocational school. Imperial College is known for being research oriented. It has one of the largest research incomes and it is one of the most technology transfer active universities in the UK. Imperial College's Technology Transfer Company was founded in 1986 and registered more than a 100 patents in 2007 alone. City University on the other hand has not been as focused on research and patenting and therefore also has a much shorter history of industry sponsored research.

2.1 Data

We have created a longitudinal dataset containing demographic characteristics, publications, research funds and patents for all the researchers employed in the Departments of Civil Engineering, Mechanical and Aeronautical Engineering and Electrical Engineering of City University of London and Imperial College London from 1985 until 2006.[4] 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). Additionally, industry collaboration of academics in engineering departments is better recorded than in other disciplines.

(1) Demographics. Research productivity might be linked to the researchers' personal attributes such as gender, education and academic rank. Of this, academic rank is the only time-variant and relevant 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. This information was taken from the universities'

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[4]For Imperial College we collected data from only 3 of their 6 engineering departments to better match the results with the 3 engineering departments at City University.

prospectuses and calendars, which are available at the British Library.[5]

(2) Publications. We collected information on all articles that were published by the aforementioned researchers while they were employed at the two institutions, and are indexed in the ISI Science Citation Index. The entrees include address data that allowed us to identify coauthors and hence we can evaluate whether they can be considered as research output with public coauthors only or also with industrial coauthors.

(3) Research Funds. We collected information on the funding that these researchers obtained from the Engineering and Physical Sciences Research Council (EPSRC), the main UK government agency for funding research in engineering and the physical sciencies. We computed the total monetary value of the research grants awarded to each staff member in our sample while they were employed at the two institutions.[6] Each award holds information on the research partners which will enable us to distinguish between funds with at least one industrial partner from those without any.

(4) Patents. We further collected patents that identify the aforementioned researchers as inventors and have been filed while they were employed at the two institutions from the European Patent Office database. We thereby did not only consider patents filed by the universities themselves but also those assigned to third parties. The filing date was chosen as it represents the closest date to invention.[7]

Research productivity. First, we use two variables as proxies for research output

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[5]Information about academic employment is given by academic year. However, subsequent information on publications and research income was collected by calendar year. Therefore employment periods were transferred into calendar years which added half a year to the start and end of each researcher's employment.

[6]The information available dates back to 1985. This is one of the reasons for the starting year of our sample. Also, from 1985 onwards, the Higher Education Funding Council for England (previously called University Grants Committee) decided to be selective in its research funding to universities. They were then induced to also seek for alternative sources of income.

[7]As in previous studies (see e.g. Fabrizio and Di Minin (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, assignee and technolgoy class for all patents potentially attributable to each inventor.

in a given year: 1. the number of publications for which the researcher is an author, regardless of the number of coauthors; and, 2. the "coauthor-weighted" sum of publications for which the researcher is an author, with the weights being the inverse of the number of coauthors. The second measure is also widely used because it avoids double counting of publications (see e.g. Hanish et al., 1998). Besides those two proxies, we use 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. This proxy allows us to adjust research productivity by its relative quality.[8] We use the ISI Impact Factor 2005, a noisy but widely accepted measure of importance attribution based on the number of citations the journals receive. Since we concentrate on only one area of research, the impact factor can be considered as fairly reliable (Narin and Hamilton 1996).

Direction of research. As an indicator of the direction of research we use widely used Patent board-NSF classification 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. We then aggregate the ranks into applied and basic research publications. In accordance with Breschi et al. (2008) we classify types 1 and 2 as applied and types 3 and 4 as basic publications.

University-industry collaboration. We define two different proxies for university-industry collaboration: the fraction of EPSRC funds with at least one industrial project partner and the fraction of academic publications with at least one coauthor from the industry. Both measures are complementary as not all industry collaboration results in co-publications (Katz and Martin, 1997). Since the 'accumulated' collaboration may capture better the true profile of the academic in terms of her collaboration with the

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[8]As an alternative measure, one could have used the number of citations of the article. This measure, however, is affected by the number of years since publication since, of course, citations accumulate over time. One would need to carefully normalise the time effects or consider a specific time-window and drop many observations (see Narin and Hamilton, 1996).

industry, we use stock specifications of these two measures. We also take a one-year lag as the effect of industry collaboration is not contemporaneous. Additionally, we allow for a differential effect for those researchers with no industry collaboration at a given time by introducing two time-variant dummy variables that take value one if the researcher does not have any EPSRC funding with an industrial partner and if she does not have any coauthor with an industrial affiliation, respectively. Finally, we also introduce two further time-variant dummy variables that take value one if the researcher has not received any funding and if the researcher has not published any paper, respectively.

Patents and academic rank. To measure the impact of academic patenting on the timing of the release of publications, we define three variables which count at time t the number of patents filed during (1) the previous year $t-1$, (2) the same year t, and (3) the following year $t+1$. We also include dummy variables for each of the academic ranks.

A formal definition of all the variables can be found in Table 1 and in the section below, we provide some summary statistics of the variables we use in our empirical analysis.

2.2 Descriptive statistics of the data

Table 2 presents descriptive statistics of our data set, with Figures 1 to 4 presenting graphically some of this information. Figure 1 shows that the total number of publications is higher for Imperial than for City partly because City University only has 97 staff member observations as opposed to 279 for Imperial. However, the average number of publications per staff member is also lower at City for most years, as shown in Figure 2. The average number of publications is steadily increasing at Imperial and it is much more volatile at City, probably because it is a smaller university and it is more affected by staff turnover.

Table 2 shows that the average number of publications per member of staff per year is significantly higher at Imperial College (1.64) than at City University (1.15). However, if one takes into account the number of coauthors, the difference is reduced to a non-significant amount. Researchers at Imperial tend to publish with more coauthors. If one adjusts the number of publications by their quality (measured through the impact factor of the journal), the difference becomes again significant: Imperial College has a

quality-adjusted average of 1.25 while City University's average is 0.98. According to our definitions of basic and applied publications, the percentage of applied is practically the same for both universities, with 79% of the total. The high percentage of applied publications is given the applied character of engineering science itself. The average EPSRC funding for Imperial College is about five times higher than that of City University (£77,230 as opposed to £16,526). Overall, these results reflect the important differences between the two universities, especially in the absolute numbers of these variables.

Our measures of university-industry collaboration, however, are not that different between the two universities. Figure 3 does not show a clear pattern as to which university has a higher percentage of publications with industry co-authors. Again Imperial seems to follow a more stable trajectory than City. Table 2 shows that on average the percentage is slightly higher for Imperial (11%) than for City (8%). The ratio of EPSRC with industry partners over all EPSRC is almost the same for both Universities and equal to about a third. Figure 4 shows that this relationship has not always been the same: City University's percentage of Industrial EPSRC is higher than that of Imperial College before 1992 and ever since 2002. Imperial's percentage of industrial EPSRC raised up until 1998 and has declined over the past 10 years.

The average number of patents differs significantly between the two institutions: 0.05 for Imperial College and 0.03 for City University. These values are nevertheless very small for both institutions (the maximum number of patents per member of staff in a year is 4 for Imperial and 2 for City).

2.3 Empirical Model

We base our empirical specification on the implicit assumption that the utility of a researcher in a given year depends on the quantity and the quality of her publications, the amount of research grants, the number of patents, and her income. Given her time constraints, the researcher chooses how much time to devote to basic and applied research, to grant applications, to teaching and to performing other administrative tasks; and to directly collaborating with the industry.

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According to the reduced form of this model, research output should depend not only on time-invariant socio-demographic characteristics, but also on time-dependant variables including the academic's degree of collaboration with industry partners and other control variables reflecting changes in her status (academic rank, etc.). Accordingly, we formulate reduced form equations for the different measures of research output as:

$$y_{it} = \alpha y_{i,t-1} + x'_{it}\beta + z'_i\alpha + \varepsilon_{it} \text{ where } \varepsilon_{it} = \mu_i + v_{it}$$

and y_{it} is the research outcome measure of academic i in year t; $y_{i,t-1}$ the research outcome measure lagged one period; x_{it} a vector of time variant explanatory variables including the stock measure of industry collaboration, measures of patent flow and academic rank; z_i contains time-invariant observed individual specific variables such as gender, education, department, and university. As usual, ε_{it} is the error term containing two terms: the academic i fixed effect μ_i and a disturbance term v_{it}. We assume that the idiosyncratic disturbances μ_i are uncorrelated across individuals.

In order to control for the potentially different effect of industry collaboration on academic outcomes for those academics that leave our sample early, either between the 1st and 5th year or between the 6th to 10th year after their arrival, as well as for those academics that join the sample after 2002, we create indicator variables for those three groups. We will interact these dummy variables with the degree of industry collaboration to control for the attrition bias.

Thus, we are faced with the estimation of a dynamic model - current realizations of the dependent variable are influenced by past ones. Moreover, some regressors may be endogeneous -.i.e., some of the time variant and invariant explanatory variables are most likely correlated with the perturbation term ε_{it}. As an example, being a professor or getting many industrial funds are most likely correlated with having a high cognitive ability, which is an unobserved factor captured in the fixed effect term μ_i. The existence of a fixed effect term in the disturbance poses additional challenges to the econometrician: even if the v_{it} are uncorrelated over time, there exists serial autocorrelation of the ε_{it}.

To ensure consistency and to solve the fixed effects induced autocorrelation of our estimates we use 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. A problem with the original Arellano-Bond estimator is that lagged levels are often poor instruments for first differences. Arellano and Bover (1995) described how one could add an equation in levels to be estimated with the equation in first differences and thereby improve the performance of the estimator, increase efficiency and reduce finite sample bias. 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). We treat the lagged number of publications, the number of patens, and the stock variables for the degree of industry collaboration as endogenous and the academic rank and year dummies as exogenous. To instrument we use all variables, the exogeneous and the lagged endogeneous ones. The inclusion of lags results in a large number of instruments. This may lead the system-GMM estimator to use too many moment conditions with respect to the number of available observations, and hence to over-fitting. Thus, we had to reduce the number of lags used to keep the number of instruments below the number of academics (i.e., the number of 'groups' we have). As a robustness check, we include estimations treating only the clearly endogenous lagged variables as instruments and all other variables as exogenous. Complementarily, we also report the results of a simple GLS with fixed effects.

Lastly, to study the impact of collaborating with the industry on the probability of the academic re-directing her/his research towards applied papers, we estimate a reduced form where the proability of producing applied research papers depends on observable characteristics, industry collaboration, and individual dummies, controlling by the year of publication.

2.4 Empirical results and discussion

In this section, we first present the estimates of the GLS with fixed effects and the two-step system GMM models to discuss the impact of industry collaboration on research

productivity in terms of quantity and quality of research output. Later on this section, we describe our findings with regards to the effect that patents have on the timing of release of the publications. Then, we comment on the estimates of the Probit model with individual fixed effects for the impact of industry collaboration on the probability of producing applied research papers. Finally, we discuss the effect that academic seniority has on research output by referring to both, the GMM and the Probit estimates.

Our main empirical results are reported in Tables 3 and 4. These tables report the estimates of six different model specifications. First, in column 1, the results of estimating a Fixed Effects GLS specification. Second, in column 2, the estimates of a GLS with Fixed Effects specification that includes the lagged dependent variable term as a regressor. Third, in column 3, the results corresponding to the estimation of a GMM model where the only endogenous variable we consider is the lagged dependent variable (number of publications). Fourth, results in column 4 correspond to the estimation of a GMM model where patents are also treated as endogenous. The fifth specification estimates displayed in column 5 considers lagged number of publications and industry collaboration as endogeneous. Finally, in column 6 we display the results of the sixth and last specification in which all three potentially endogenous variables as endogeneous, i.e. lagged number of instruments, patents, and industry collaboration.

For all GMM specifications, we report the Arellano-Bond tests and the Sargan/Hansen tests at the bottom of Tables 3, 4 and 5. 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.

For simplicity, most of the discussion of the results in terms of the impact of industry collaboration on research output will focus on the estimates of the sixth specification in Tables 3 and 4. We believe that this is the better specification in terms of unbiasedness and consistency of the coefficients. The other specifications are included as robustness checks.

Research productivity. Table 3 shows the impact on the number of publications of

industry collaboration, measured by the *lagged accumulated fraction of EPSRC funding with the industry* and Table 4 reports the *lagged accumulated fraction of industry co-authored papers* . The estimate for the constant term can be considered as our "baseline" or benchmark prediction for a researcher with a minimal but positive degree of industry collaboration. The last column in Table 3, for instance, shows that a researcher who has a marginal fraction of her overall previous EPSRC funding with industrial partners is predicted to publish 2.934 articles per year. Two and a half publications (-2.491) are subtracted if she had no past EPSRC funding. Thus, an academic who has not obtained any kind of EPSRC funding up to the previous year publishes significantly less. More surprisingly, researchers who obtained only non-industrial funding in the past are also likely to publish significantly less than their peers with a small fraction of funding with industrial partners. Those with only non-industrial past funding have one and a half publication (-1.527) subtracted from the benchmark. As the fraction of industrial collaboration increases though the number of publications decreases, at an average rate of -3.035. In an extreme case where all the previous EPSRC funding included industrial partners (so that the variable industry collaboration equals 1), the number of publications is predicted to fall below zero (2.934-3.035=-0.101).[9][10]

The other specifications presented in Table 3 show similar results, however, as displayed in column 4 where we consider industry collaboration as an exogenous variable but past publications and number of patents as endogenous, the number of predicted publications for the extreme case of Degree of Industry Collaboration equaling one would be close to one (1.649-0.697-0.802). This result is similar to the number of publications

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[9]This predicted value turns negative due to the relatively low number of observations with a high degree of industry collaboration. The estimate should therefore be taken with caution.

[10]As an exercise, we calculate the 'steady state' level of publications for any given level of industry collaboration. We do that for the benchmark case of a Lecturer. Taking the estimates in column 5 of Table 3, the steady state number of publications would be equal to$[\frac{2.934}{(1-0.273)} - \frac{3.035}{(1-0.273)} \times$ Degree of industry collaboration$]$, or $[4.035 - 4.17 \times$ Degree of industry collaboration$]$. Thus, again in the long run, the maximum number of publications would be achieved at a minimal level of industry collaboration. But, as for the short run estimate, having no external funding would be 'bad' too in terms of publications as then -1.527 or -2.941 would be additionally substracted from the long run baseline of 4.035.

predicted if the academic had had EPSRC funding without industrial involvement, but higher than if she had had no previous EPSRC funding at all.

Note that the GMM estimates of the impact of industry collaboration on publications is much more negative in the final specifications (last two columns of Table 3) than otherwise. Our interpretation of this is that it corroborates the endogeneity of industry collaboration.[11] The GMM estimates in column 3, correct for the endogeneity of the lagged dependent variable, but not that of industry collaboration. So, if industry collaboration and past publications are positively correlated through an unobservable time variant factor affecting both of them positively - say accumulated 'expertise'- then, the estimate of the impact of the industry collaboration will be biased upwards reflecting the positive effect of that omitted time variant factor on current publications. Once the endogeneity of industry collaboration is accounted for (in the estimates showed in last two columns), its effect becomes necessarily more negative. This 'negativization' effect can be observed for both the continuous variable 'Degree of industry collaboration', and the indicator variables 'No EPSRC' and 'No industry collaboration' as they become also more negative when their endogeneity is controlled for.

As explained before, to control for the attrition bias in our sample, we interact the degree of industry collaboration with a dummy for those academics who left their institution within the first five years of joining and also with a dummy for those who left it between 6 and 10 years after they joined. Given that our sample ends in 2006, we also interact it with a dummy for those academics who enter our sample after 2002. As we can see from the significance levels of the estimates, the results for the *leavers* and the *newcomers* are not significantly different from those for the benchmark academics present through all the sample.

The results in Table 4 indicate that our results are robust to the alternative definition of industrial collaboration based on the fraction of co-authored publications with the industry. Looking again at the first row of the last column of this table, we see that the

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[11]Given that, as expected, past publications significantly explain current publications, the first two columns present the estimates of misspecified models.

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baseline annual number of publications according to this model is 2.199; not having had any previous publication has also a very negative effect on that publications' benchmark (-1.804); and, not having had any publication co-authored with an industrial partner before also subtracts a fair amount of publications (-1.355). Further, the number of annual publications increases significantly for low levels of industrial involvement as compared to none at all: it declines at a rate of -2.705 with the fraction of industrial coauthored papers. For all four GMM models, we get negative predicted numbers of publications for higher levels of industry collaboration. This is partly due to the low number of observations for such higher levels but also because of the interdependence between the lagged dependent variable and the industry coauthor measures. However, our estimates indicate that researchers that publish a small fraction of their articles with industrial coauthors publish more than their counterparts with a larger fraction and more than those without any industrial coauthors at all.[12]

In Table 5 we report several alternative specifications to check the robustness of our model. To simplify, we only use the *fraction of past accumulated EPSRC with industrial partners* as a measure of industry collaboration and omit the results with the industry coauthor measure. The GMM models' results in columns 1 to 5 instrument for all potentially endogenous variables and hence they compare to column 6 in Tables 3 and 4.

Results of the model in column 1 include interaction terms for City University to allow results to vary by university. Imperial College's estimates are reflected in the main effects' coefficient and those of City University in the interaction terms. The impact of industrial collaboration on publications is qualitatively the same in the two institutions. However, having no previous funding at all has a significantly more negative coefficient for those at City than for those at Imperial. Having had no previous industrial involvement also has a worse effect on publications for those at City than those of Imperial, but the difference is not significant. The marginal effect of industry collaboration on research productivity is

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[12]Nevertheless, since the sample average of industry collaboration is about 0.31 when measured through the lagged accumulated fraction of industrial EPSRC funds and just 0.08 when measured using publications with industrial co-authors, we are aware that implications at the extremes should be interpreted with caution.

more positive for City but again not significant. The number of instruments in this model outnumbers the number of groups and might therefore suffer from over-fitting. However, it was not possible to reduce the number of instruments further. Summarising, despite their different characteristics the overall pattern of the impact of industry collaboration is similar at both institutions.

In column 2 of Table 5 we report the estimates of a model that uses a stock of industry collaboration lagged three periods as opposed to one. As reported, that reduced the coefficient for lagged number of publications (from 0.332 to 0.239), but leaves the degree collaboration impact quite unchanged (-2.312 instead of -2.334). Also column 3, which reports our model when excluding all those members of staff with little research activity (those who publish less than 3 papers throughout their career), finds similar results. Here, the number of publications does not turn to a negative value for industrial collaboration equal to one. Again, for this model, the number of instruments is rather large as compared to the numbers of researchers and results might suffer an over-fit.

Table 5 further checks whether our results are robust to changes in the measure of 'academic output'. In the forth column we use the '*inverse of the number of coauthors-weighted*' number of publications as the dependent variable of the model to avoid double counting of publications. In the fifth column we use the *impact-factor-weighted number of publications* to capture the quality of the publications. As can be seen in column 4, impact of industry collaboration on the coauthor weighted publications is similar to the results reported in column 6 of Table 3. The default number of weighted publications is 1.150, not having had yet any previous industry collaboration makes the expected weighted number of publications drop by a significant -0.523. Not having had any EPSRC has an even more negative effect on the baseline number of weighted publications (-0.866). Weighted publications then decline at a rate of -1.182 with lagged accumulated fraction of industry collaboration. The effects are again qualitatively similar to those of the original specification.

Column 5 of Table 5 shows the impact of industry collaboration on the 'impact factor' weighted number of publications. According to this model, the baseline number of

publications is 5.442 per year, not having had industry collaboration and not having had any EPSRC have very negative effects on this number (-3.802 and -4.973, respectively). The quality adjusted number of publications declines then at a rate of -5.488 with increasing intensity of collaboration with the industry. Again, those researchers that have the highest predicted quality weighted number of publications are those that have had previous funding with a minimal part linked to industrial partners. However the lagged number of publications does not have a significant influence on the current year's number of publications.

In sum, results in Tables 3 and 4 and columns 1 to 5 in Table 5 suggest that not having any industrial contact has a very negative impact on academic output. But, at the same time, academic output is higher for low degrees of industry involvement as compared to high levels of industrial collaboration. All tables show that the results do not differ much between the different specifications of our GMM model and neither do they differ when using different specifications of our measures of research output or industry collaboration.

Skewing effect. Column 6 of Table 5 presents the estimates of the impact of industry collaboration on the probability of an applied publications using a Probit model with individual dummies to control for fixed individual effects. To estimate this model, we only consider observations for which we have information on the publication type in terms of appliedness/basicness. Focussing on the marginal effects, we find a significant negative relationship between the likelihood of publishing an applied paper and having no EPSRC funding and no prior industry collaboration (–0.164 or 16.3% and -7.4% lower probability). This shows that having had no previous funding or only public funding can be associated with a higher probability of producing basic research. However, the impact of the degree of industry collaboration on the probability of applied publications is negative by decreasing it by up to a 30%. This result suggests that low levels of industry involvement can be associated with higher applied research but that high levels of collaboration increase the likelihood of producing basic publications. This result might be biased due to the selection bias created by having to drop those publications for which we have no information and by the low number of observations with high degree of industry involvement. Thus, they

need to be taken with caution. Additionally, the patent variables' coefficient show that having filed a patent the previous year increases the probability of producing applied publications. Thus, this suggests that filing patents may indeed be costly in terms of future basic research.

Secrecy effect. Table 3, 4 and 5 also include patent variables which help to analyse the impact of patenting on the number of publications. We hypothesized that patenting might delay publications as only unpublished information can be patented. Therefore we expect that the number of publications is below average the years contemporaneous and previous to the year of producing a patent because publications might be held back. Consistently, we expect the number of publications to be above average the year after filing a patent. The results for the fixed effects model as well as the GMM estimates indicate indeed that having filed patents in the previous year has an overall positive effect on the number of publications. This might indicate that publications are delayed until the patent is filed and then published subsequently. The estimates however are only significant if we consider patents exogenous variables and do not instrument them. Thus, it seems that the significance of patents is merely picking up the significance of some unobserved other individual characteristic that influences patents and publications.

Results of the fixed effects regressions additionally indicate that in the year before filing a patent researchers publish less than in a usual year. This again could indicate that publications are held back until the application has been filed. Regardless, neither of these estimates do stand up to scrutiny in our main model in column 6. Column 1 of Table 5 again shows that the effect of patenting are very different for the two universities. The results seem to be driven by City University researchers who publish significantly more the year after they filed a patent, while patenting has no effect on publications numbers at Imperial College whatsoever. The difference to City University staff can be explained by the low number of patent observations for City University. We therefore conclude that it is difficult to draw conclusions regarding the secrecy hypotheses, and if anything we would tend to reject it given this evidence.

Demographic variables Both institutions show that the number of publications, whether we adjust by the number of coauthors or by the quality of the journal, or not, increases with seniority. Professors publish more than readers, which in turn publish more than senior lecturers and lecturers. However, the difference between lecturers and senior lecturers is only significant in the fixed effects model but not for any of the research output measures in the GMM regressions. Also Applied-ness cannot be associated with seniority but seems unaffected by a researchers rank.

3   Concluding Remarks

Our main results for this panel indicate that researchers benefit from collaborating with the industry. Researchers with no industrial involvement are likely to be those with the least research outcome in both universities. Nevertheless, high levels of industrial involvement affect negatively research productivity in terms of number of publications - be this number measured crudely or be it weighted by the inverse of the number of co-authors or the impact factor of the publishing journal. 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 - e.g., through Transfer of Technology and Knowledge programs - is a beneficial policy not only per se but also for academic productivity. But, doing so without at the same time providing incentives to publish academic research papers may have a perverse effect and harm the quantity and quality of academic research output. Finally, discouraging high levels of industry collaboration may also be advisable if research output is a desired objective.

Our conclusions have to be taken with caution. First of all, our sample although larger than any used so far, may still be small. Second, further research is warranted on how to accurately measure research output and the degree of external funding, including industry collaboration. Although this is a limitation, results obtained using all research funding information for City University are qualitative similar to those using only EPSRC funding.

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Figure 1: Total Number of Publications
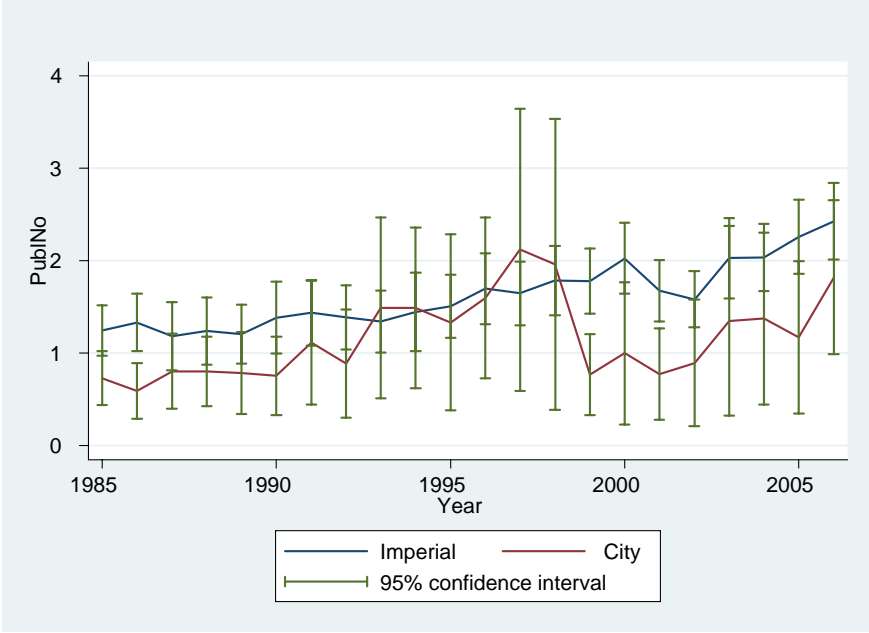

Figure 2: Average Number of Publications (per staff)
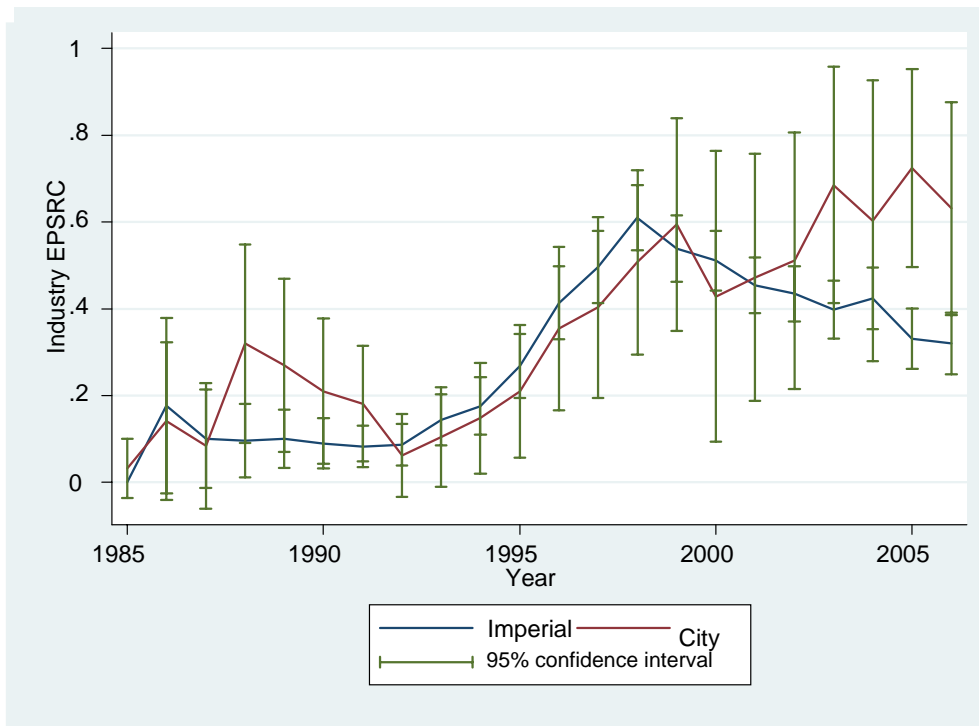
Figure 3: Average % of EPSRC with Industry (per staff)
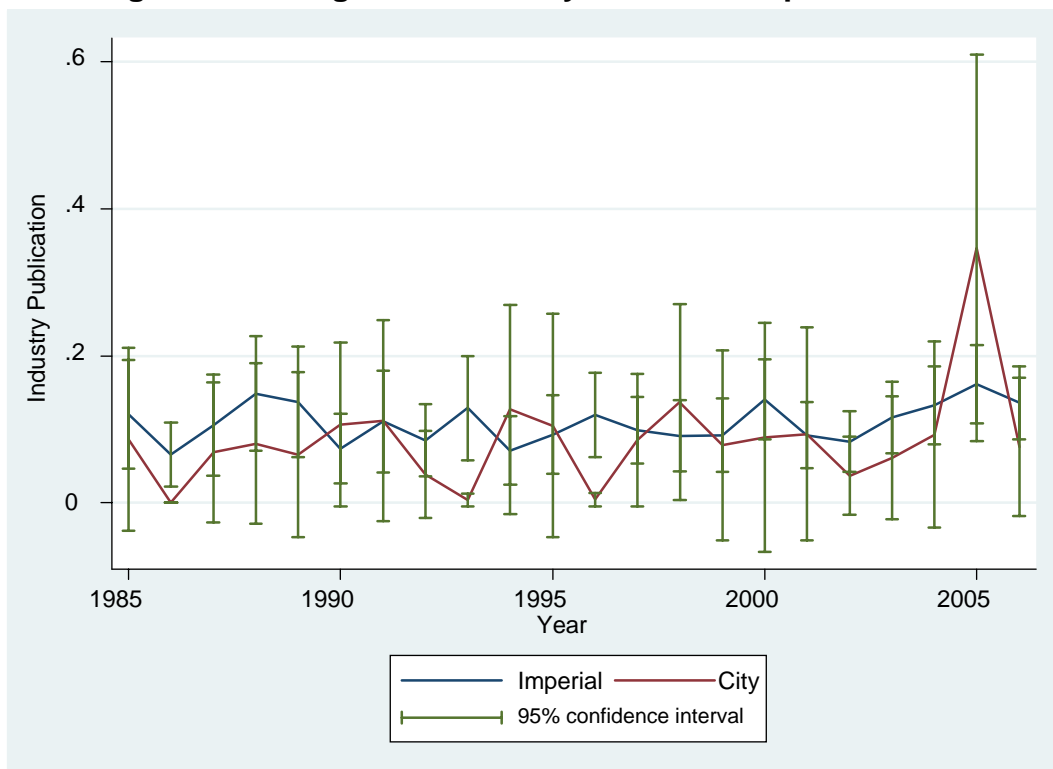

Figure 4: Average % of industry co-authored publications

Table 1: Variables used in descriptive statistics and GMM estimation

Variable	Description
Dependent Variables	
Publications	Number of publications by individual i corresponding to observation period t
Co-author weighted publications	Number of publications by individual i corresponding to observation period t weighted by the inverse of the number of co-authors
Impact Factor weighted publications	Number of publications by individual i corresponding to observation period t weighted by the Impact Factor of the journal
Fraction of applied publications	Fraction of applied publications by individual i in observation period t
Categorial Variables	
Leavers 1-5yrs	Individuals i that left the sample after 1 to 5 years
Leavers 6-10yrs	Individuals i that left the sample after 6 to 10 years
Newcomers after 2002	Individuals i that joined the sample after 2002
Industry EPSRC	
Value of EPSRC funds	Amount of total EPSRC funding in GBP received by individual i in observation period t
Fraction of EPSRC funds with industry collaboration	Fraction of EPSRC funds with one or more industrial partners received by individual i in observation period t
Degree of industry collaboration	Moving fraction of accumulated EPSRC funds with one ore more industrial partners received by individual i up to period $t-1$
No industry collaboration	Equals 1 if no EPRSC funds involved the industry up to period $t-1$; 0 otherwise
No EPSRC	Equals 1 if no EPSRC funds were received up to period $t-1$; 0 otherwise
Industry Co-author	
Fraction of publications with co-authors from the industry	Fraction of publications with one or more industry co-authors published by individual i in observation period t
Fraction of co-author weighted publications with co-authors from the industry	Fraction of publications with one or more industry co-authors published by individual i in observation period t and weighted by the inverse of the number of co-authors
Fraction of Impact Factor weighted publications with co-authors from the industry	Fraction of publications with one or more industry co-authors published by individual i in observation period t and weighted by the Impact Factor of the journal
Degree of industry collaboration	Moving Fraction of accumulated publications with one or more industry co-authors published by individual i up to period $t-1$
Quadratic Term	Square of 'Degree of industry collaboration'
No industry collaboration	Equals 1 if no publications were industry co-authored up to period $t-1$; 0 otherwise
No Publications of any	Equals 1 if there were no publications up to period $t-1$; 0 otherwise
Released patents	
Number of patents filed previous year	Number of patents filed by individual i in period $t-1$
Number of patents filed this year	Number of patents filed by individual i in period t
Number of patents filed following year	Number of patents filed by individual i in period $t+1$
Academic Rank	
Lecturer	Equals 1 if individual i is Lecturer in period t; 0 otherwise (Benchmark)
Senior Lecturer	Equals 1 if individual i is Senior Lecturer in period t; 0 otherwise
Reader	Equals 1 if individual i is Reader in period t; 0 otherwise
Professor	Equals 1 if individual i is Professor in period t; 0 otherwise

Table 2: Descriptive Statistics

Variable	City University				Imperial College				Comparison
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean Diff. (Imperial - City)
Number of publications	1.15	2.8	0	34	1.64	2.21	0	16	0.497 (0.083)***
Number of co-author weighted publications	0.65	1.27	0	12.5	0.7	0.95	0	7	0.048 (0.037)
Number of Impact Factor weighted publications	1.209	3.835	0	45.954	1.892	4.245	0	62.606	0.682 (0.146)***
Value of EPSRC funds (in £1000)	16.32	33.02	0	271.45	77.23	149.1	0	2138.22	60.703 (45.59)***
Fraction of applied publications	79.3%	34.3%	0.0%	100.0%	79.4%	35.2%	0.0%	100.0%	0.001 (0.020)
Fraction of publications with coauthors from the industry	8.2%	24.2%	0.0%	100.0%	11.6%	25.4%	0.0%	100.0%	0.028 (0.013)**
Fraction of EPSRC funds with industry collaboration	31.5%	43.1%	0.0%	100.0%	33.8%	38.6%	0.0%	100.0%	0.023 (0.022)
Number of patents filed this year	0.03	0.18	0	2	0.05	0.27	0	4	0.024 (0.008)***

The total number of observations for City University is 1088 (97 academics); for Imperial College it is 3097 (279 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: Impact of industry-collaboration - measured as % of industrial EPSRC over all EPSRC - on Number of Publications

	GLS with Fixed Effects	GLS with Fixed Effects	GMM (Instrumenting for Publications)	GMM (Instrumenting for Publications and Patents)	GMM (Instrumenting for Publications and Industry Collaboration)	GMM (Instrumenting for Publications, Patents and Industry Collab)
Constant	1.758	1.477	1.649	1.582	2.939	2.934
	(0.243)***	(0.240)***	(0.255)***	(0.280)***	(0.624)***	(0.607)***
Publications (t-1)		0.197	0.232	0.234	0.274	0.273
		(0.018)***	(0.069)***	(0.069)***	(0.074)***	(0.079)***
Industry collaboration						
No EPSRC	-0.924	-0.758	-1.296	-1.178	-2.519	-2.491
	(0.191)***	(0.188)***	(0.250)***	(0.252)***	(0.692)***	(0.675)***
No industry collaboration	-0.639	-0.516	-0.697	-0.706	-1.593	-1.527
	(0.149)***	(0.147)***	(0.215)***	(0.212)***	(0.491)***	(0.446)***
Degree of industry collaboration	-0.840	-0.704	-0.802	-0.718	-3.062	-3.035
	(0.257)***	(0.252)***	(0.334)**	(0.346)**	(0.921)***	(0.945)***
Interaction for Leavers 1-5yrs	0.697	0.694	0.168	0.092	2.017	-0.505
	(1.472)	(1.444)	(0.410)	(0.375)	(5.019)	(5.822)
Interaction for Leavers 6-10yrs	0.550	0.467	-0.295	-0.404	2.326	2.072
	(0.662)	(0.649)	(1.000)	(0.481)	(1.869)	(1.819)
Interaction for Newcomers 2002	-0.304	-0.575	dropped	dropped	dropped	dropped
	(1.697)	(1.666)				
Released patents						
Number of patents filed previous year	0.082	0.117	0.345	0.060	0.404	0.091
	(0.131)	(0.128)	(0.154)**	(0.184)	(0.158)**	(0.180)
Number of patents filed this year	-0.220	-0.156	0.197	-0.309	0.276	-0.210
	(0.132)*	(0.130)	(0.141)	(0.169)*	(0.162)*	(0.225)
Number of patents filed following year	-0.286	-0.311	-0.043	0.252	-0.068	0.063
	(0.133)**	(0.131)**	(0.161)	(0.631)	(0.183)	(0.616)
Academic Rank						
Senior Lecturer	0.598	0.458	0.100	0.089	-0.047	-0.024
	(0.120)***	(0.118)***	(0.094)	(0.098)	(0.129)	(0.126)
Reader	1.240	0.949	0.687	0.582	0.463	0.470
	(0.147)***	(0.147)***	(0.153)***	(0.174)***	(0.170)***	(0.174)***
Professor	1.907	1.470	0.872	0.819	0.523	0.593
	(0.192)***	(0.193)***	(0.184)***	(0.234)***	(0.212)**	(0.221)***
Observations	3442	3442	3091	3091	3091	3091
Number of ID	348	348	325	325	325	325
Number of Instruments			220	133	256	305
AR1 test z (p-value)			-5.09 (0.0000)	-5.00 (0.0000)	-5.05 (0.0000)	-5.01 (0.0000)
AR2 test z (p-value)			0.87 (0.3850)	0.85 (0.3976)	0.99 (0.3242)	0.95 (0.3427)
Sargan test p-value			0.3923	0.1960	0.3396	0.7747
R-squared (within)	0.07	0.10				
R-squared (between)	0.11	0.35				

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

All models include year dummies. The category LECTURER is the omitted category in the Tenure scale. GMM instruments are lagged values of the left hand side variables. For GMM estimates, the finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005) is used. Inactive Staff -or those having no publications and no EPSRC funds- are excluded

Table 4: Impact of industry-collaboration - measured as % of Publications with Industry Coauthors - on Number of Publications

	GLS with Fixed Effects	GLS with Fixed Effects	GMM (Instrumenting for Publications)	GMM (Instrumenting for Publications and Patents)	GMM (Instrumenting for Publications and Industry Collaboration)	GMM (Instrumenting for Publications, Patents and Industry Collab)
Constant	1.543	0.948	1.734	1.638	2.142	2.199
	(0.246)***	(0.248)***	(0.283)***	(0.288)***	(0.442)***	(0.418)***
Publications (t-1)		0.201	0.230	0.235	0.265	0.259
		(0.019)***	(0.069)***	(0.069)***	(0.069)***	(0.071)***
Industry collaboration						
No Publications	-0.728	-0.207	-1.336	-1.084	-1.849	-1.804
	(0.202)***	(0.205)	(0.297)***	(0.275)***	(0.472)***	(0.458)***
No industry collaboration	-0.501	-0.202	-1.005	-0.923	-1.361	-1.355
	(0.150)***	(0.150)	(0.273)***	(0.257)***	(0.407)***	(0.405)***
Degree of industry collaboration	-1.191	-0.720	-2.096	-1.779	-2.624	-2.705
	(0.446)***	(0.440)	(0.647)***	(0.617)***	(1.261)**	(1.238)**
Interaction for Leavers 1-5yrs	-0.529	-0.754	-1.330	-1.709	-5.067	-5.013
	(3.948)	(3.876)	(1.426)	(1.161)	(6.678)	(10.336)
Interaction for Leavers 6-10yrs	-0.871	-1.158	-1.306	-1.108	0.588	0.388
	(1.227)	(1.205)	(1.164)	(1.080)	(1.407)	(1.286)
Interaction for Newcomers 2002	-0.648	-0.819	dropped	dropped	dropped	dropped
	(2.415)	(2.371)				
Released patents						
Number of patents filed previous year	0.080	0.113	0.323	-0.008	0.346	0.060
	(0.131)	(0.129)	(0.150)**	(0.189)	(0.150)**	(0.184)
Number of patents filed this year	-0.206	-0.148	0.177	-0.331	0.188	-0.231
	(0.132)	(0.130)	(0.143)	(0.173)*	(0.153)	(0.218)
Number of patents filed following year	-0.281	-0.306	-0.075	0.337	-0.132	-0.114
	(0.133)**	(0.131)**	(0.162)	(0.628)	(0.177)	(0.601)
Academic Rank						
Senior Lecturer	0.533	0.449	0.012	0.034	-0.119	-0.125
	(0.121)***	(0.119)***	(0.100)	(0.107)	(0.115)	(0.113)
Reader	1.179	0.954	0.606	0.488	0.376	0.401
	(0.150)***	(0.149)***	(0.155)***	(0.176)***	(0.182)**	(0.181)**
Professor	1.874	1.487	0.847	0.862	0.663	0.713
	(0.195)***	(0.195)***	(0.177)***	(0.198)***	(0.216)***	(0.225)***
Observations	3442	3442	3091	3091	3091	3091
Number of ID	348	348	325	325	325	325
Number of Instruments			220	133	253	302
AR1 test z (p-value)			-5.22 (0.0000)	-5.15 (0.0000)	-5.34 (0.0000)	-5.27 (0.0000)
AR2 test z (p-value)			0.96 (0.3368)	0.93 (0.3544)	1.16 (0.2449)	1.11 (0.2679)
Sargan test p-value			0.2250	0.2015	0.1869	0.3720
R-squared (within)	0.07	0.10				
R-squared (between)	0.11	0.40				

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

All models include year dummies. The category LECTURER is the omitted category in the Tenure scale. GMM instruments are lagged values of the left hand side variables. For GMM estimates, the finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005) is used. Inactive Staff -or those having no publications and no EPSRC funds- are excluded.

Table 5: Impact of industry-collaboration measured as % of industrial EPSRC over all EPSRC

	GMM (with University Interactions)		GMM (3 year stock of industry collaboration)	GMM (excluding those with few publications)	GMM	GMM	Probit	
	Dependent Variable: Publications		Dependent Variable: Publications	Dependent Variable: Publications	Dependent Variable: Coauthor Weighted Publications	Dependent Variable: Impact Factor Weighted Publications	Dependent Variable: Applied-ness	
	Main Effect	Interaction for City					Coefficients	Marginal Effects
Constant	2.454 (0.457)***		2.697 (0.564)***	2.844 (0.630)***	1.150 (0.200)***	5.442 (1.438)***	0.502 (0.626)	
Dependent Variable (t-1)	0.332 (0.040)***		0.239 (0.072)***	0.269 (0.079)***	0.234 (0.055)***	0.008 (0.112)		
Industry collaboration								
No EPSRC	-1.694 (0.467)***	-0.868 (0.429)**	-2.226 (0.638)***	-2.261 (0.705)***	-0.866 (0.222)***	-4.973 (1.495)***	-0.467 (0.183)**	-0.163 (0.068)**
No industry collaboration	-1.172 (0.382)***	-0.297 (0.433)	-1.623 (0.514)**	-1.279 (0.478)***	-0.523 (0.182)***	-3.802 (1.222)***	-0.226 (0.119)*	-0.074 (0.039)*
Degree of industry collaboration	-2.334 (0.730)***	0.294 (0.826)	-2.312 (0.771)***	-2.712 (1.016)***	-1.182 (0.400)***	-5.488 (1.861)***	-0.958 (0.265)***	-0.307 (0.084)***
Released patents								
Number of patents filed previous year	0.075 (0.186)	1.633 (0.321)***	-0.101 (0.566)	0.093 (0.182)	0.108 (0.083)	0.070 (0.402)	0.174 (0.083)**	0.055 (0.026)**
Number of patents filed this year	-0.081 (0.235)	1.837 (0.331)***	-0.280 (0.203)	-0.211 (0.179)	-0.016 (0.106)	-0.689 (0.558)	-0.124 (0.084)	-0.039 (0.027)
Number of patents filed following year	0.284 (0.499)	-0.989 (0.672)	-0.081 (0.189)	0.095 (0.591)	-0.014 (0.292)	-0.218 (1.187)	-0.015 (0.087)	-0.005 (0.028)
Academic Rank								
Senior Lecturer	-0.091 (0.123)		0.018 (0.111)	-0.048 (0.129)	-0.027 (0.057)	-0.084 (0.160)	-0.081 (0.133)	-0.026 (0.044)
Reader	0.401 (0.169)**		0.717 (0.191)***	0.438 (0.184)**	0.217 (0.078)***	0.603 (0.282)**	-0.172 (0.129)	-0.057 (0.044)
Professor	0.511 (0.204)**		1.012 (0.229)***	0.617 (0.225)***	0.283 (0.092)***	1.188 (0.474)**	-0.140 (0.163)	-0.045 (0.052)
Observations	3093		2464	2751	3091	3091	3245	
Number of ID	325		272	268	325	325		
Number of Instruments	464		260	302	305	305		
AR1 test z (p-value)	-5.82 (0.0000)		-4.95 (0.0000)	-5.02 (0.0000)	-6.25 (0.0000)	-1.92 (0.0553)		
AR2 test z (p-value)	1.56 (0.1190)		1.62 (0.1044)	0.91 (0.3631)	0.29 (0.7752)	-0.99 (0.3239)		
Sargan test p-value	1.0000		0.3911	0.9672	0.7715	0.6215		
Pseudo R-squared							0.2100	
Predicted p							0.7450	
Log likelihood							-1588.3864	

Robust standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

All regressions include year dummies, and Interactions with dummy variables for Leavers and Newcomers. The category LECTURER is the omitted category in the Tenure scale. Probit Regressions include group dummies. GMM instruments are lagged values of the left hand side variables. For GMM estimates, the finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005) is used. Inactive Staff -or those having no publications and no EPSRC funds- are excluded.