University Research and Industry Involvement. Three Essays on the Effects and Determinants of Industry Collaboration and Commercialisation in Academia.

A Thesis
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by

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DECLARATION

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SUMMARY

This thesis investigates the factors influencing an academic's involvement with industry and how these collaborations affect research outputs in terms of publications and patents. It employs a longitudinal dataset that comprises more than 4000 engineering academics over 20 years and a smaller subsample of 479 academics over 12 years and uses robust econometric approaches to address issues of unobserved heterogeneity and endogeneity. Collaboration with industry is measured through two funding modes: (1) funding received from industry directly and (2) funding from the research council that involves business partners. The thesis is unique in its ability to measure two distinct types of funding over a long time period and compare these to commercialisation efforts of academics. It analyses the relationship between both activities and relates it to academics' publication numbers. Considering all three activities jointly allows some new insights into their complementarities as well as identifying possible substitution effects.

CHAPTER I

INTRODUCTION TO THE THESIS

1.1 Background

Modern science and technology industries have been built on the expertise of university research and science has long been an important factor for economic growth in modern, knowledge based economies. Discoveries at research institutions provided the basis for many new commercial opportunities leading to the development of new industries (in the case of biotechnology or microelectronics) or transforming existing ones. However, since the publication of some blockbuster patents that earned inventors and their universities hundreds of millions of dollars, the commercial prospects of university research have come to be a major focus of government policy. Academic research is no longer undertaken for the sake of creating knowledge alone but increasingly driven by the needs of industry and its market value.

Driven by economic changes in the 1970s which saw industries under-investing in research and university budgets shrinking (Geuna, 2001), over the past three decades policy makers have emphasised that links between the science base and industry would improve economic growth and competitiveness. Encouraging such links and the successful commercialisation of university inventions have since become major policy goals in the US and in Europe. Governments across the world are providing incentives for researchers to engage in research partnerships with industry, to undertake projects with greater commercial prospects, and to patent scientific research.

Policy makers hope that such links could provide commercially exploitable academic knowledge for industry, and new sources of funding for university research (Gibbons and Johnston, 1974; Poyago-Theotoky et al., 2002). In the UK, for instance, since the 1980s government reports have emphasised the importance of university-industry partnerships and research driven by "societal needs" and "technology foresight" (Tapper, 2007). Financial incentives were given to encourage such initiatives and legislation in the vein of the Bayh-Dole Act introduced to enable universities to develop commercial activities. Also, the number of directed research grants increased dramatically, all with the implicit aim to steer research in the government's policy direction (Tapper, 2007), albeit with mixed success (Cervantes, 1998).

Policy initiatives were largely initiated based on anecdotal evidence of commercial success in the US, despite ambiguous empirical evidence. Several papers reported that governments held unrealistic expectations regarding income generated from licensed inventions and contract research (Feller, 1990; Nelson, 2001, 2006) and that it is unclear whether the Bayh-Dole Act made a real difference (Mowery et al., 2001). Yet, universities across Europe are transforming and making wealth creation and societal impact their "third mission".

In this introductory chapter I give a brief overview over different arguments regarding the benefits and risks of university-industry collaboration for the individual scientists and introduce some existing empirical evidence. I point out the drawbacks of empirical analysis and give suggestions for solving these problems (section 2). Having set the backdrop of this thesis I specify the purpose of my work, give a brief overview over the three papers and present the contributions of this PhD work (section 3). Section 4 finally summarises the implications for the policy agenda. The most important conclusion is that there still is more need for empirical analysis and appropriate data.

1.2 Empirical Analysis of University-Industry Collaboration

1.2.1 Benefits and Concerns for Academic Researchers

While many government policies to encourage science-industry links and commercialisation seem sound at the macroeconomic level, they assume that the research agendas of academics can be influenced by monetary incentives. There is evidence, however, to indicate that academic scientists, unlike researchers in industry, value independence in choosing their research agenda more highly than monetary rewards (Levin and Stephan, 1991). The question then arises, how does industry collaboration and patenting relate to the traditional publication based reward structure and the researcher's intrinsic motivation to publish? The two main challenges for empirical research, thus, are (1) to identify those factors that steer academics towards commercialisation and collaboration, and (2) to identify potential negative consequences for academic research.

In many subject areas, including engineering and material science, industry links are inevitable and indeed much of the research would not be possible without the input of industry partners. In a survey of 671 academic scientists and engineers, Lee (2000) reports securing of funds for equipment and research assistants as the principal reason for collaboration with industry, leading to more autonomy and flexibility for academic researchers. Additionally, contacts to industry allow insight into applied research processes providing new ideas for research.

However, concerns over patenting and an increased involvement with industry, especially with regard to limitations imposed on knowledge dissemination and choice of research topics, at the expense of "open science" and fundamental research, have been addressed by several scholars (Bok, 1982; Dasgupta and David, 1994; Feller, 1990; Florida and Cohen, 1999; Nelson, 2001, 2004; Poyago-Theotoky et al., 2002). It is feared that applied sponsors and commercial objectives may influence the performance of academics, diverting their attention away from scientific research, as well as shifting their choice of research topic towards an applied approach. Initial survey results by Blumenthal et al. (1986) confirmed these concerns, with researchers reporting that industry collaboration has a negative impact on their research productivity and that it skews their research towards applied topics.

These concerns have been picked up by empirical analysis with a large number of papers investigating a potential trade-off between patenting and academic research output (for a recent review see Baldini (2008) and Foray and Lissoni (2010)). Most of these studies, however, find a positive link between patenting and publications (e.g. Azoulay et al., 2009; Bercovitz and Feldman, 2008; Calderini et al. 2007; Stephan et al., 2007; Zucker et al., 1998). Empirical work has also failed to find any evidence for a shift towards applied research (e.g. Thursby and Thursby, 2007).

While the link between patenting and publications is well researched, there is little empirical work on how they are linked to other forms of knowledge transfer. Indeed, the lack of such studies is considerable given the potential negative effect of industry collaboration on academia and the fact that it is far wider spread amongst academics than patenting (Agrawal and Henderson, 2002; Geuna and Nesta, 2006). While some papers argue that so called star researchers are most attractive to industry (Zucker et al., 1998), Goldfarb (2008) finds that mid-level researchers attract the majority of applied funding. A recent study by Thursby and Thursby (2010) finds a positive link between publications, patents and industry funding suggesting that all three activities are complementary.

Most of the existing evidence is based on cross-sectional data or case studies and does not consider the dynamics of the research process, making it difficult to draw strong conclusions for future research. The focus has largely been on the coexistence of different academic and commercial activities without tracing the effect of increases in collaboration and changes in policy directives. There is, hence, a further requirement for longitudinal studies on the effects and determinants of industry collaboration. The next section will discuss in more detail some of the pitfalls in the empirical analysis of the relationship between industry involvement and scientific work.

1.2.2 Drawbacks of Empirical Analysis

Though a large body of literature has approached the topic of industry involvement and its effect on individual academics, empirical analysis has been faced with a range of methodological problems, not all of which it has been able to solve.

Firstly, measurement problems are encountered in empirical analysis. The scientific research process is characterised by a multitude of research inputs and outputs, and most studies have only been able to collect a small proportion of these. It has been acceptable practice for empirical studies to use bibliometric measures of research activity, publication and patent numbers, in the analysis of university-industry collaboration, due to their accessibility. However, researchers also supply teaching, contract research and consulting, and apply for research grants, all of which are information which very few studies have been able to consider. Collection of such data has been limited to surveys and cross-sectional analysis, which are limited in size and unable to address changes in scientific research. Therefore, the development of indicators, other than patent and publication metrics, for possible channels of industry involvement should remain the foremost aim of economic analysis in this field. As Geuna and Nesta (2006: 805) stated: "there is an urgent need for more reliable and more useful data (on a time series basis) to be collected, not only on IP activity, but also on the inputs and outputs of the other activities carried out by researchers and research organisations."

In addition to measurement problems, we encounter problems in determining the direction of causality. Any factor can be considered both as an input and an output of scientific research. For example, the current levels of funds are determined by past levels of publications, and are likely to influence future levels of publications. This causes problems of reverse causality and potential endogeneity (Bonaccorsi and Daraio, 2003). A potential endogeneity problem further arises, as both funding and publications may be influenced by unobserved factors, such as a researcher's ability. It is imperative that economic analysis takes these effects into account if it is to achieve robust results, and a majority of existing studies has failed to do so. In order to solve endogeneity it is important to find instrumental variables, to control for previous states of research activity, and to exploit the effect of exogenous and over-time variation in academic research. It is therefore most desirable to collect longitudinal data on academic activity to be able to solve the different causes of endogeneity.[1]

A third problem relates to the dynamic nature of the research process. The distribution of publications, patents, and industry grants amongst researchers is highly skewed and current levels of activity are intrinsically linked to past levels (e.g. Blundell et al., 1995). So far, very few studies have considered dynamic feedback to academic research in their analysis of university-industry collaboration. Additionally, we encounter unknown and variable time-lags between inputs and outputs of research and differing short and long term effects (Bonaccorsi and Daraio, 2003). It is therefore important to consider long time-series to be able to consider varying time-lags, and to explore the systematic changes in university-industry collaboration.[2]

Though a large number of empirical studies have tried to analyse the relationship between industry-collaboration and academic research, most have failed to consider all three problems of econometric analysis addressed above.

Additional to these methodological problems a further issue derives from the explicit

[1] Attempts to solve the endogeneity in the scientific research process have been made by Fabrizio and DiMinin (2008) using lags of university patents as instruments, Goldfarb et al. (2009) using lagged venture capital and patents by peers as instruments, and by Breschi et al. (2008), Franzoni et al. (2009) and Azoulay et al. (2009) using inverse probability of treatment weights to predict selection into patenting. The validity of these approaches, however, has been questioned (Foray and Lissoni, 2010).

[2] Agrawal and Henderson (2002) is one of the very few papers considering dynamic feedback and varying time-lags in its analysis and finds the lagged dependent variable to have a stronger impact than other factors.

focus on developments in the US. As Europe has a very different university, funding, reward and patenting structure, it is difficult to directly transpose results from the US to the European environment. It is therefore essential to perform more robust analysis on European data with large longitudinal datasets, both using existing indicators and producing new ones.

1.3 Contribution of This Thesis

1.3.1 Purpose

In light of the issues addressed above, this PhD thesis is particularly interested in the analysis of individual academics in the UK collaborating with industry. It aims to identify those factors steering researchers towards collaboration and patenting, and to analyse the importance of industry involvement for scientific research.

The discussion thus far has indicated that there is more need for data and studies on industry collaboration to contribute to the current debate on the role of the university. This thesis has the ambition to address these issues by investigating the collaboration and patenting behaviour of engineering academics in the UK. As one of the first countries in Europe to adopt policies supporting academic involvement in knowledge transfer, the UK presents an interesting case to study. It is also of interest in view of future developments for the rest of Europe (see appendix A for a detailed description of policy developments in the UK).

The thesis firstly contributes by presenting new longitudinal data that takes into account existing and new indicators for industry collaboration. It uses funding data to measure involvement with industry, and shows that this activity is indeed far more widespread than patenting. This thesis follows other studies on patenting in Europe by considering all patents with a university inventor, and confirms that for the UK the majority of academic patents are owned by industry (see Appendix B for a detailed description of the data and the data collection process as well as its limitations).

Using this data this thesis tries to identify and characterise those researchers that are likely to engage in collaborative and commercial projects. It further examines some of the recent concerns by analysing the impact of collaboration and commercialisation on academic research output, and the circumstances under which individual researchers can benefit from these. Specifically it tries to answer the following three questions:

(1) What developments have there been in industry funding and collaborative and commercial research in the UK?

(2) What affects a researcher's engagement in different forms of industry collaboration and commercialisation?

(3) What are the effects of collaboration and commercialisation activities on scientific productivity?

In order to answer these questions I pursue a robust, empirical analysis of the data. Using time-series I am able to consider the dynamic nature of the research process and try to address potential endogeneity issues. The database provides a method of controlling for reverse causality and enabling me to separate effects and determinants of university-firm alliances.

1.3.2 Outline

This thesis consists of three papers. The first paper examines the effects of industry collaboration on academic research output. Specifically, we study the impact of university-industry research collaborations via research council sponsored funding partnerships, on academic output, in terms of productivity and direction of research. We use panel data techniques to control for heterogeneity and consider dynamic feedback by including lags of the dependent variable, and endogeneity by using lags of the regressors as instruments. Using the difference generalized method of moments (GMM) estimator we compare the effects of instrumenting for some of the explanatory variables on the results. The main findings suggest that researchers collaborating with industry publish more than their peers. However, this positive effect decreases for higher levels of industry involvement, once we control for the endogeneity of research funding. Moreover, is this the first evidence to firmly establish the presence of a "skewing" effect, suggesting that growing ties with industry "skew" research towards a more applied approach. Considering funding partnerships also diminishes the effect of patenting on publication numbers, indicating that it is far more important for predicting research outputs than other forms of knowledge transfer.

The second paper tries to identify the factors that explain researchers' involvement with industry through two different channels of collaboration, (1) direct funding from industry and (2) research council sponsored collaboration. Specifically, it studies how publication and patenting histories enable access to different types of collaborative funding. Using the system GMM estimator it considers the dynamic feedback of past collaboration and endogeneity. I use lags of endogenous variables and several exogenous factors, e.g. lags of department publications and patents as well as lagged differences of department wealth and regional business enterprise R&D, as instruments. As different types of funding may act as complements I additionally estimate a system of simultaneous equations using 3SLS. The results show that collaboration through research council sponsored programmes is closely related to scientific activity in terms of publication numbers. I further find that patents can help leverage direct industry sponsorship. This evidence is supportive of hypotheses that direct collaboration requires a different set of skills and that science oriented academics engage in symbolic partnerships via the research councils.

The third paper investigates the increasing commercialisation of academic research by looking at the effect of industry funding and publications on a researchers' patenting activities. The paper employs a different approach to panel data estimation that uses pre-sample information of the dependent variable to control for heterogeneity (Blundell et al., 1995). It further attempts to account for the large number of zeroes in the data by modeling their source using zero inflated regression techniques. The findings indicate that funding from industry has a strong effect on the number of patents generated and that industry partners can spur academics towards commercialisation. Publication numbers can be helpful in explaining an academic's overall research activity and hence propensity to produce potentially patentable research. However, not all publishable research is also patentable and I show that only high impact research can increase the number of patents.

1.3.3 Contributions

The main contributions of this thesis are represented in a few key points.

1. It provides new longitudinal data and presents new indicators for university-industry collaboration.

2. It provides evidence for the importance of using robust empirical methods that specifically take into account the potential endogeneity problem and unobserved heterogeneity.

3. It finds that industry collaboration through funding partnerships is an important factor for determining the number of publications and patents. Funding, in both cases, is found to be most influential and the often reported link between publications and patents is less strong than indicated by previous papers.

4. It also shows that publications and patents differently affect the access to various types of university-industry collaboration. Patents have a positive impact on the receipt of direct funding from industry, while publications positively affect the propensity to engage in EPSRC sponsored collaborations. This points out the importance of considering different types of collaborations, and makes restrictions on the applicability of some of my results on other forms of knowledge transfer.

1.4 Concluding Remarks

The findings of this thesis suggest that encouraging collaboration with industry is a beneficial policy but also show that not all types of collaboration are equally beneficial. Moderate collaboration mediated by the research councils increases publications, while direct funding from industry seems to rather increase the number of patents.

Policy makers in the UK have been pushing for more collaboration and commercial applicability in research. I show that both are linked and that it is beneficial to further encourage commercialisation of research if a new funding regime is desired. However, the focus on collaborative research may also be contra-productive as it seems to push researchers towards symbolic partnerships to conform to the new requirements of the UK funding and research councils.

I also find some evidence that the continuous support through non-competitive grants is key for providing academics with good basis for external research funding acquisition. This policy recommendation contradicts the current efforts of the UK funding councils to reduce non-competitive grant allocation.

CHAPTER II

THE IMPACT OF INDUSTRY COLLABORATION ON ACADEMIC RESEARCH: EVIDENCE FROM THE UK (WITH ALBERT BANAL-ESTANOL AND MIREIA JOFRE-BONET)

2.1 Introduction

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

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

[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 emanating from federally funded research; (ii) the National Cooperative Research Act (1984) that reduced antitrust penalties from engaging in research joint ventures; (iii) the Omnibus and Trade and Competitiveness Act (1988) that established the Advanced Technology Program, which supports collaborative research projects in generic technologies. During this decade, the National Science Foundation also substantially increased the funding for University-Industry Cooperative Research Centers.

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

The increased incentives (and *pressures*) to collaborate with industry have controversial side effects on the production of scientific research itself. Nelson (2004) argues that industry involvement might delay or suppress scientific publication and the dissemination of preliminary results, endangering the "intellectual commons" and the practices of "open science" (Dasgupta and David, 1994). Florida and Cohen (1999) claim that industry collaboration might come at the expense of basic research: growing ties with industry might be affecting the choice of research projects, "skewing" academic research from a basic towards an applied approach.

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

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

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

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

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

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

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

Our results bolster empirical evidence from previous surveys and cross-sectional studies by establishing a causal relationship between collaborative research and academic output. Some studies suggest that industry involvement is linked to higher academic productivity (e.g. Gulbrandsen and Smeby, 2005; Thursby and Thursby, 2010).[4] Once controlling for endogeneity, we still find supportive evidence for the positive impact of the presence of collaboration on research output. The negative effect of the intensity of collaboration is also consistent with survey results (Blumenthal et al., 1986, 1996a) and cross-section empirical evidence (Manjarres-Henriquez 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]

The second main contribution of this paper is to show that industry collaboration has a negative effect on the number of basic research articles while it increases the more applied type of research publications. These results are consistent with the "skewing" effect of industry involvement on direction and focus of research pointed out by questionnaire data studies. Blumenthal et al. (1986) and Gulbrandsen and Smeby (2005), for example, report that the choices of research topics of academics whose research is supported by industry were biased by their commercial potential. Instead, the empirical papers using patenting and licensing as measures of industry involvement fail to find evidence of a negative effect of patenting on the number of basic publications (Breschi et al., 2008; Calderini et al. 2007; Hicks and Hamilton, 1999; Thursby and Thursby, 2002, 2007; van Looy et al., 2006).[6] We believe that our findings are the first to firmly establish the presence of a "skewing" effect.

[4] 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".

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

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

The third contribution of this study is to compare and separate out the effects of collaboration sponsored through research grants with industrial partners from the effects of patenting. After controlling for the dynamic nature of the publication process and the endogeneity of partnerships with the industry, we find that patenting does not hinder or delay the publication of research results but does not affect it positively either. These findings diverge from most recent empirical studies suggesting a positive relationship between patenting and publication rates (Azoulay et al., 2009; Breschi et al., 2008; Calderini et al. 2007; Fabrizio and DiMinin, 2008; Stephan et al., 2007; van Looy et al., 2005).[7] Our results are most consistent with those of Agrawal and Henderson (2002), who found that patenting did not affect publishing rates of 236 scientists in two MIT departments in a 15-year panel, and those of Goldfarb et al. (2009) who report similar results for the effect of licensing on the number of publications for 57 inventors at Stanford University in an 11-year panel.

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

2.2 Empirical Strategy

2.2.1 Data

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

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

We retrieved names and academic ranks of university researchers from university calendars.[8] We focused on academic staff carrying out both teaching and research and did not consider research officers or teaching assistants. Whenever possible, we obtained full names (first and last name), when not possible, we had to record last names with the two initials of the first name. We followed the researchers' career paths between the different universities in our dataset.[9] Academics leave (and join or rejoin) our dataset at different stages in their career, when they move to (or from) abroad, industry, departments other than engineering (e.g. chemistry, physics, computer science), or universities not part of our dataset. In total we collected 7,707 individuals, 5,172 of which remain in our dataset for six years or more. They represent the basis for our data collection and enable us to retrieve information on publications, research funds and patents.

Publications. Data on publications was derived from the ISI Science Citation Index (SCI). The number of publications in peer-reviewed journals even if not the only measure is the best recorded and the most accepted measure for research output as publications are essential in gaining scientific reputation and for career advancements (Dasgupta and David, 1994). We collected information on all the articles published by researchers in our database while they were employed at one of the 40 institutions in our sample. Most entries in the SCI database include detailed address data that allowed us to identify institutional affiliations and unequivocally assign articles to individual researchers.[10]

Research funds. The information on industry collaborations are based on grants given by the Engineering and Physical Sciences Research Council (EPSRC), the main UK government agency for funding research in engineering and the physical sciences. Each award holds information on research collaborators, and grants with one or more industry partner are considered "collaborative grants". As defined by the EPSRC, "Collaborative Research

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

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

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

Grants are grants led by academic researchers, but involve other partners. Partners generally contribute either cash or 'in-kind' services to the full economic cost of the research." The EPSRC encourages research in collaboration with the industry. As a result, around 35% of EPSRC grants presently involve partners from industry. The volume of EPSRC grants with industry partners cannot be taken as a proxy for direct funding from the industry. But, since the EPSRC is by far the largest provider of funding for research in engineering (amounting to around 50% of overall funding), these mediated partnerships allow for a very comprehensive (and homogeneous) insight into the dynamics of university-industry collaborations. Our database contains information on start year and duration of the grant, total amount of funding, names of principal investigators and co-investigators, institution of the principal investigators (the grant receiving institution), and names of partner organisations. Data on these grants is available from 1986 onwards.

Patents. Patent data was obtained from the European Patent Office (EPO) database. We collected those patents that identify the aforementioned researchers as inventors and were filed while they were employed at one of the 40 institutions. We not only consider patents filed by the universities themselves but also those assigned to third parties, e.g. industry or government agents. The filing date of a patent was recorded as representing the closest date to invention. Since the filing process can take several years, we were only able to include patents awarded by 2007, hence filed before 2005.[11] The EPO covers only a subsample of patents filed with the UK Intellectual Property Office (UKIPO). Nevertheless, those patents that are taken to the EPO may probably be those with higher economic potential and/or quality (Maurseth and Verspagen, 2002).

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

[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 to exclude others with similar or identical names. This was done comparing address, title and technology class for all patents potentially attributable to each inventor. The EPO database is problematic in that many inventions have multiple entries. It was therefore necessary to compare priority numbers to ensure that each invention is only included once in our data.

projects, and 1,828 patents.

2.2.2 Variables and Descriptive Statistics

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

Research output. As a measure of research output, we consider the normal count of publications (the number of publications for which the researcher is an author) in accordance with the majority of studies on industry collaboration. However, publication counts might be misleading for articles with a large number of authors and may not reflect a researcher's effective productivity. We therefore additionally obtain the "co-author-weighted" count of publications for which we weight a publication associated to an academic by the inverse of the publication's number of coauthors.[12]

Kelchtermans and Veugelers (2009) find that (non-collaborative) funding has a different impact on research quantity than on research quality. To investigate the question whether researchers with links to industry publish articles of lower quality we use the "impact-factor-weighted" sum of publications (with the weights being the impact attributed to the publishing journal) as an additional proxy of academic publishing activity. To do so, we use the SCI Journal Impact Factor (JIF), a measure of importance attribution based on the number of citations a journal receives to adjust for relative quality. Though not a direct measure for quality, the JIF represents the importance attributed to a particular article by peer review. As the JIF of journals differs between years, and journals are constantly added to the SCI, we collected JIFs for all the years 1985-2007, to capture all SCI journals and to allow for variation in the impact factor.

Figure 1 shows that the average number of publications per staff was rising continuously over the sample period, in both the Russell Group and the Non-Russell Group of

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

universities.[13] Table 2 shows the all-time averages and the differences between the two groups of universities and it shows that the average number of publications per member of staff per year is significantly higher for the elite Russell Group of universities (1.67 vs. 1.10). The difference in publications between the Russell Group universities and the rest stays significant even after we take into account the number of coauthors (0.61 vs. 0.42) or we adjust for quality (1.77 vs. 0.97).

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

Collaborative research and patents. Principal investigators and co-investigators on sponsored projects are understood to contribute to the research project and benefit from generated outcomes. To account for the participation of all investigators, we divided the total monetary income from the research grants between the principal investigator (PI) and her named co-investigator(s). Although we include co-investigators as beneficiaries of the grant, we positively discriminated PIs by assigning them half of the grant value and splitting the remaining 50% amongst their co-investigators. PIs are assigned a major part of the grant as they are expected to be responsible for the leadership of the research and to profit most from a successful partnership. We additionally spread the grant value over the whole award period, i.e., if the grant is 2 years we split it equally across those 2 years, if it is over 3 or more years, the first and the last years (which are assumed to not

[13] Several papers have documented a trend towards increasing multi-co-authorship (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.

represent full calendar years) receive half shares and it is otherwise split equally across the intermediate years.[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.

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

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

As mentioned above, we aim to separate the effect of patenting from the effect of industry collaboration. To measure the impact of academic patenting on timing and rate of publications, we use the number of patents filed during the same year and the two years preceding the publication. Researchers in Europe, unlike the US, cannot benefit from a "grace period" and hence they have to withhold any publication related to the patent until the patent is filed. Publications might be released once the patent is filed. We therefore expect a lag of up to 2 years between invention and publication in a journal. We can

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

see from Table 2 that the average number of patents differs significantly between the two groups of universities (0.04 vs. 0.03). The values are very small for both groups but the average number of patents filed by researchers has increased substantially over the past 20 years and in particular after 1995 (from 0.03 in 1985 to 0.06 in 2003).

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

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

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

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

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

2.2.3 Empirical Model

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

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

To estimate how collaboration with the industry affects research output, we estimate a dynamic model where current publications are influenced not only by past publications but also by the degree of collaboration with industry. We choose a specification that allows current publications to be affected by the existence and the intensity of collaborative funding. To do so, we include a dummy for having had any type of EPSRC past funding in the last five years, another dummy for having had EPSRC funding with industry partners, and then a variable that measures which fraction of the overall funding was joint with industry. By including a dummy (intercept) and a continuous variable (slope), we intend to capture the trade-off of industry collaboration on publications described above. [15]

Accordingly, we formulate our reduced form equations as:

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

where y_{it} represents academic i's research output at time t, $fund_{it}$ is an indicator variable for having received EPSRC funds; $ifund_{it}$ is an indicator variable for having received EPSRC funding with industry partners; ic_{it} measures the *intensity* of the collaboration with industry; p_{it}, are indicator variables for having filed patents; and x_{it} is a vector time-variant explanatory variables including tenure rank. Since the distribution of grants and academic research output has been found to be highly skewed (D'Este and Fontana, 2007), we take logarithms of both measures. The error term contains two sources of error: the academic i's fixed effect term μ_i, and a disturbance term v_{it}. Thus, even if the fixed idiosyncratic disturbances μ_i are uncorrelated across individuals, they create autocorrelation of the errors over time.

To estimate the model above we need to use a method that corrects for fixed effects induced autocorrelation, for the endogeneity of the lagged dependent variable, and, very importantly, for the endogeneity of industry collaboration, patents, and academic rank.[16] For these methodological reasons, we chose to estimate the model using the GMM based

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

[16] Publishing, getting many industrial funds, producing patens and being a professor, for example, may all due to having a high cognitive ability, which is unobserved.

Arellano-Bond estimator (Arellano and Bond 1991; Blundell and Bond 1998) and use lagged endogenous variables and exogenous variables as instruments, which ensures the consistency of the estimates. We treat as endogenous variables the lagged number of publications, the number of patents, industry collaboration and academic rank. Year dummies and department size are used as exogenous additional instruments.

The GMM estimator treats the model as a system of equations – one for each time period – where 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 which takes 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.

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

2.3 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.

2.3.1 Main Results

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

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

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

Having had funding in the last 5 years: As expected, the existence of any funding in the past five years enhances research productivity in all four specifications. In the GLS specification the "had some funding" coefficient is significant and equals 0.0309, indicating that if an academic had received funding she publishes, on average, around 3% more articles than if she did not receive any funding at all. If we take into account the dynamic nature of the publishing process but not the fact that industry collaboration and patents may be endogenous (second column's specification), funding does not have any significant impact on the number of publications. However, as soon as we take into consideration that funding and collaboration are endogenous (columns three and four), the coefficient becomes significant again.

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

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

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

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

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

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

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

2.3.2 Differences across Academics

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

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

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

Looking at the third block of results, we can see that the coefficients for senior staff (Readers and Professors) are larger than in the benchmark model and that they differ significantly from the coefficients for junior academics (Lecturers and Senior Lecturers).

Firstly, the impact of having received funding on the number of articles is more positive for senior academics (0.390, equivalent to an increase of 39% of the constant) as is collaboration with industry (0.163 equivalent to a further 16%). Also, the effect of the intensity of a researcher's involvement in collaborative research is more negative than that of the benchmark (elasticity of -0.729). Junior staff on the other hand 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.

2.3.3 Weighted Number of Publications

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

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

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

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

2.3.4 Basicness of Publications

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

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

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

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

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

2.4 Discussion and Conclusion

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

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

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

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

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

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

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

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

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

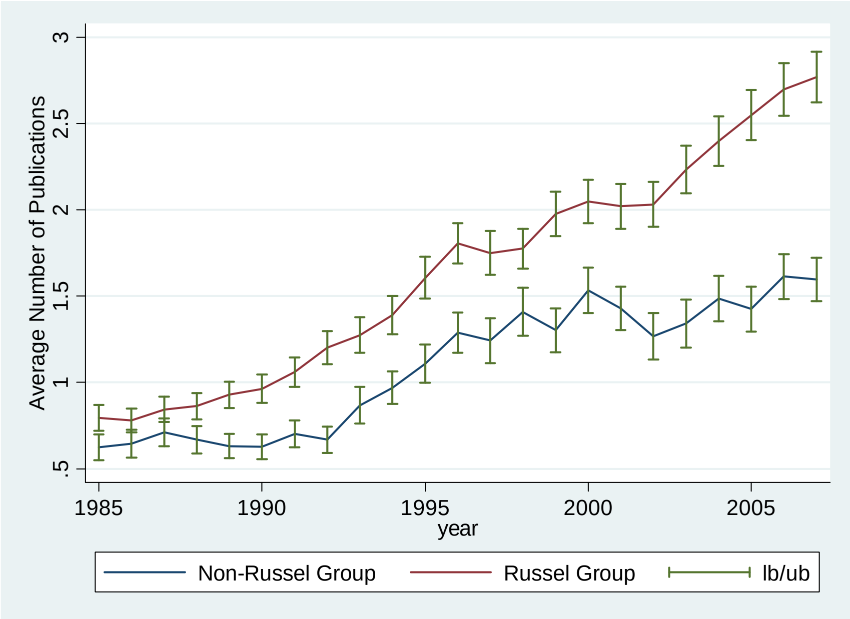

Figure 1: Average number of publications per faculty member.

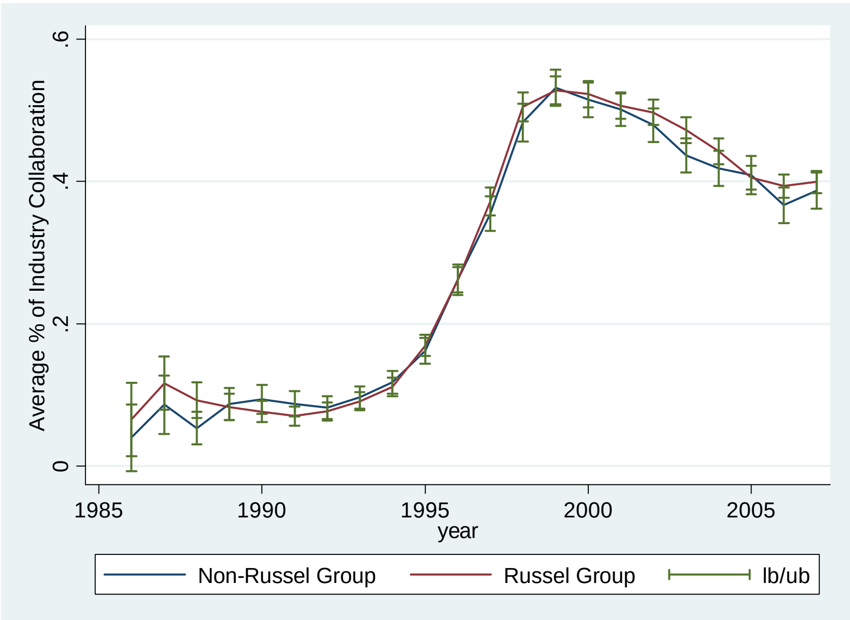

Figure 2: Average percentage degree of industry collaboration based on EPSRC funds

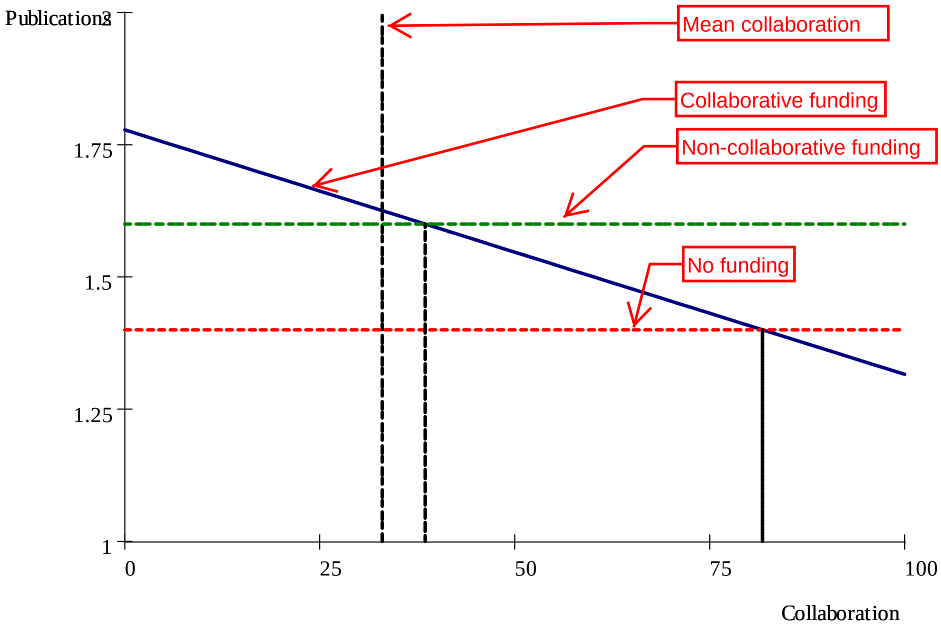

Figure 3: Predicted number of publications for any degree of industry collaboration.

Table 1: List of universities

Russell 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 Manchester 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	Non-Russel Group Std.Dev.	Non-Russel Group Min	Non-Russel Group Max	Russel Group Mean	Russel Group Std.Dev.	Russel Group Min	Russel Group 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.

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

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

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

	(1) GMM - Interaction with Russell Group		(2) GMM - Interaction with Stars		(3) GMM - Interaction with Seniors	
	Russell Group Effect	Non Russell Group	Stars Effect	Non Stars	Seniors Effect	Juniors
Constant	0.313***		0.265***		0.313***	
	[0.0444]		[0.0721]		[0.0468]	
Lagged Dependent Variable						
Ln (publications)$_{t-1}$	0.0204		0.0648		0.061	
	[0.0600]		[0.0595]		[0.0710]	
Ln (publications)$_{t-2}$	0.0532***		0.0544***		0.0589***	
	[0.0116]		[0.0117]		[0.0119]	
Collaborative Research						
Had some funding$_{t-1}$	0.129*	0.0243	0.404	-0.297	0.390***	-0.193**
	[0.0733]	[0.0791]	[0.405]	[0.419]	[0.0910]	[0.0757]
Had some funding with Industry$_{t-1}$	0.119*	0.00471	0.190**	-0.087	0.163*	-0.0176
	[0.0718]	[0.111]	[0.0904]	[0.108]	[0.0951]	[0.132]
Ln (fraction of accumulated 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 on industry collaboration

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

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

Table 6: Regressions of the number of publications for different classes of "basicness".

	(1) GMM Applied technology	(2) GMM Basic technology	(3) GMM Applied science	(4) GMM Basic science
Constant	0.0563	0.0608	0.0579	0.0712*
	[0.0712]	[0.0919]	[0.0578]	[0.0423]
Lagged Dependent Variable				
Dependent Variable$_{t-1}$	0.0588***	0.123***	0.0873**	0.0601
	[0.0215]	[0.0234]	[0.0339]	[0.0436]
Dependent Variable$_{t-2}$	0.0014	0.0554***	0.0691***	0.0571**
	[0.0178]	[0.0175]	[0.0250]	[0.0286]
Collaborative Research				
Had some funding$_{t-1}$	0.0547	0.159**	0.0344	-0.0347
	[0.0558]	[0.0709]	[0.0523]	[0.0370]
Had some funding with Industry$_{t-1}$	0.115**	0.0279	0.0261	0.0151
	[0.0502]	[0.0634]	[0.0454]	[0.0286]
Ln (fraction of accumulated 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

CHAPTER III

THE IMPACT OF RESEARCH PRODUCTIVITY ON GRANTSMANSHIP: CAN INDUSTRY COLLABORATION CHANGE THE FACE OF SCIENCE?

3.1 Introduction

In the past three decades universities and other public research institutions have witnessed a push for greater industrial involvement and relevance in research. In the UK for instance, several policies in the 1990s directly sought to favour research relevant to technological foresight and responsive to the needs of industry. The government initiated grants dedicated to university-industry interactions. As a consequence contacts with agents outside the university are encouraged and given a place in universities' organisational structure by being increasingly recognised in staff promotion (Kitagawa, 2010). In addition, business aspects of university research have been considered in the recent Research Assessment Exercise (RAE) and will be used for the allocation of quality related block grants by the funding councils (DIUS, 2008).

These developments have led to new opportunities for academic researchers, who are given additional support and credit for working with industry. However, not all researchers engage in collaboration activities equally. According to Owen-Smith and Powell (2001a), knowledge transfer to industry requires a very different set of skills compared to traditional academic research and only few academics may produce research that attracts industry funding. Some studies have argued that firms considers academic quality when searching for a research partner (Blumenthal et al., 1996b; Zucker et al., 1998) and that patents can help to attract consulting and research contracts with industry by increasing an academic's visibility status and providing credibility to research projects (Audretsch et al. 2006, Jensen and Thursby, 2001; Owen-Smith and Powell, 2001a). There is, however, still little empirical evidence on the real effects of publications and patents on a researcher's propensity to engage in collaboration with industry.

Much of the existing empirical literature has focussed on the relationship between patenting and publications and often considered patenting as a channel for collaboration. This has been shown to be a misapprehension and that other channels of knowledge transfer are far more important. Academics collaborate with industry through joint research projects, consulting and staff exchanges (Agrawal and Henderson, 2002; Arundel and Geuna, 2004; Cohen et al., 1998, 2002).

It has to be noted, that not all researchers engage in collaboration via the same interaction channels and at the same rate (D'Este and Patel, 2007; Link et al., 2007), and that these channels may fulfil different collaboration needs and hence appeal to different academics (D'Este and Perkmann, 2010; Perkmann and Walsh, 2009). Further, as argued by Bercovitz and Feldman (2008) and Tartari et al. (2010), some researchers might feel pressured to collaborate with industry and other external partners and engage in partnerships purely for symbolic reasons to conform to new requirements. These academics may use different types of interactions compared to their peers that are committed to industry. Publications and patents, in this context, could be considered as indicators of a researcher's scientific and commercial interest. They signal research priorities to a potential sponsor and may anticipate the researcher's disposition to engage in different types of funding partnerships. Estimating the effect of publications and patents on different channels of collaborations may thus help to identify the collaboration preferences and opportunities of different types of academics.

This paper considers the effect of publications and patents on two types of industry involvement on the individual level: (1) collaborative research projects financed and led by industry, and (2) collaborative research projects financed by the research councils. Both can be considered as indicative of the nature of research and the level of involvement of the industrial partner and represent examples of two distinctly different approaches to industry collaboration. Using data of a 12 year panel of 479 engineering academics in the UK and employing GMM and 3SLS estimations to account for endogeneity, I find that the impact of publications and patents differs for the two channels of collaboration, .

My results show that publication numbers have a positive impact on the receipt of research council sponsored collaborative funding. Direct industry funding on the other hand is not affected by publication numbers. This contradicts existing survey evidence that finds that publications are negatively correlated to industry grants (Blumenthal et al., 1996a), but also other empirical studies finding a positive effect of publication numbers on direct funding from industry (Thursby and Thursby, 2010). The effect of publications seems to differ substantially with the channel of collaboration and more science oriented researchers seem to engage in partnerships mediated by a public agent, perhaps for symbolic reasons as suggested by Tartari et al. (2010).

I further find a positive impact of patenting on direct funding from industry as previously suggested by Owen-Smith and Powell (2001a). I hence give evidence that commerce oriented researchers are also more likely to engage in direct contracts with industry. This confirms results by Thursby and Thursby (2010) for a panel of US researchers that does not control for individual or time fixed effects, as well as findings by Crespi et al. (2010) that analyses a sample of UK researchers, however, without accounting for the effect of publications.

The remainder of the paper is organised as follows. Section 2 gives details on the data used and discusses the factors influencing collaboration with industry. I further describe the empirical strategy employed and introduce the different empirical methods. In section 3 I present the results, section 4 discusses and section 5 concludes.

3.2 Empirical Strategy

3.2.1 Data and Descriptive Statistics

A longitudinal dataset of 479 academic engineers from 10 UK universities for the years 1996 to 2007 is utilised to investigate the impact of publications and patents on industry collaboration. This data represents a sub-sample of a larger database collected at City University as part of a project sponsored by the Economic and Social Research Council (ESRC). The original database was reduced as data on funding partnerships for a sufficiently long period was only provided by 10 institutions. They include 6 large engineering departments with more than 100 academics (at 3 Russell group universities and 3 technical institutions) and 4 smaller departments (at other UK universities) (see Table 7 for a list of universities). The original data was collected based on staff registers in academic calendars and the name entries used as basis for gathering publications, patents and research council funding information for the period 1985 to 2007 (for a detailed description see

Banal-Estanol et al. (2010)). 10 departments in this original sample of 40 provided information on funding received from industry, government and public bodies for the years 1996 to 2007. This information was matched with entries in the original database. The final dataset used in this analysis contains information on two channels of university-industry involvement: (1) contract research through direct funds from industry and (2) joint research sponsored by the Engineering and Physical Sciences Research Council (EPSRC). I only consider academics that remain in the sample for 10 years or more.

3.2.1.1 Variables

Below I describe the measures used in the analysis. Descriptive statistics for different collaboration channels, funding and research output measures are presented in Table 8.

Collaboration Measures. Collaboration measure 1 is based on direct funds from industry which account for approximately 9.5% of all research grant income in the sample. This type of funding can be considered as indicative of application oriented research aimed at solving specific problems of industry (Perkmann and Walsh, 2009; Thursby and Thursby, 2010). 57% of researchers receive this type of funding at least once during the sample period. The average amount of industry funding a researcher receives each year is £21,352.

Collaboration measure 2 is based on grants from the Engineering and Physical Science Research Council (EPSRC), a publicly-funded agency and the principal funding body for engineering sciences in the UK. 83% of researchers in the sample are principle investigators (PI's) on at least one EPSRC funded project during the 12 year period, which reflects the importance of the funding body for academic engineers. Again, 84% of these researchers (70% of the total sample) receive EPSRC funds that involve partners from industry at least once during the sample period. Though a non-governmental body, the EPSRC has been required to promote knowledge transfer by, for example, increasing the level of collaborative funding (DfE, 1993; RCUK, 2006). It has, since the 1990s, increasingly sought to encourage partnerships between academia and other social actors (users of research) including the health sector, industry, government, local authorities and not-for-profit organisations and the service sector. Now, almost 45% of all funds involve partners from outside academia. The average volume of collaborative EPSRC grants per academic per year is £77,876. These partnerships are typically led by the academic while industry partners contribute with additional resources and hence may represent research targeted towards less application oriented research (Perkmann and Walsh 2009). It could further be indicative of collaboration sought for symbolic reasons (as described by Bercovitz and Feldman (2008) and Tartari et al. (2010)) to conform to the requirements of the university or the EPSRC.

For both measures I only consider projects for which the researcher is principal investigator and collect information on award date, grant period and funding amount. Co-investigators could not be considered because not all 10 universities were able to supply this information.

In addition I obtain data on other, non-collaborative grants, including grants awarded by the EPSRC that do not involve industry partners, awards from other public bodies (e.g. trusts, charities) and grants from applied government agencies and government departments (e.g. MoD). While the first represents more basic research, funding from applied government agencies is mission oriented and might be comparable in nature to funding from industry (Goldfarb, 2008).

The majority of researchers in the sample receive funding from more than one type of funding agent during the observation period. 12% of researchers, however, receive no funding at all. Of those that receive funding at least once, 78% work with industry through at least one of the two collaboration channels. 45% engage in both forms of knowledge transfer during the sample period.

Research Output Measures. I define two different measures for research productivity: publications, representing academic output, and patents, as measure for commercial output. Publications were obtained from the ISI Science Citation Index (SCI), which includes journals based on a selection and reviewing process and serves as a quality indicator for publications of high scientific value.

Patents were collected from esp@cenet developed by the European Patent Office (EPO). The web interface allows searches for patents filed with the EPO but also such filed with the UK Intellectual Property Office (UKIPO) and other national patent offices. Data construction required a manual search in the inventors' database to identify those entries that were truly the academic. This was done comparing address, title and technology class for all patents potentially attributable to each researcher. As each invention can lead to multiple patents I additionally verified each entry with the Derwent World Patents Index (DWPI) that contains information grouped around a base patent, thus enabling me to uniquely identify the original invention and avoid multiple counts.

In my sample 91% of researchers publish at least one paper, and 21% file at least one patent during the observation period. The average number of publications per researcher per year is 2.19, with the average number of patents being 0.08. Patenting activity hence still presents a minor part of a researcher's work even in applied disciplines like engineering.

The average number of publications and patents over a 3 year period is calculated to account for a researcher's recent research profile.

Individual, Departmental and University Measures. Literature has identified other individual, departmental and university specific characteristics that may influence an academic's research behaviour. Amongst individual characteristics academic rank is the only time-variant factor and hence most important to my analysis. As a measure for experience it has been found to correlate positively with individual productivity and access to grants (Lee and Bozeman, 2005). However, having reached professorship there might be less incentive to perform and hence a decrease in research activity also in view of increasing administrative tasks (Levin and Stephan, 1991).

It has further been argued that individual characteristics can only partly explain research behaviour due to its collective nature (Stephan, 1996) and several papers have stressed the importance of the laboratory in research (Dasgupta and David, 1994; Stephan and Levin, 1997). It is therefore of importance to account for network or laboratory size when analysing access to funding. In this paper I use the amount of external funding available to the department as well as the average amount of university income per academic as a measure for size and research activity at department and university level. This information was collected from the 2001 and 2008 RAE submissions and from the Higher Education Statistics Agency (HESA).

3.2.1.2 Collaboration Channels and Research Productivity

Table 9 reports the mean statistics for research output and funding variables. The figures give the average numbers per academic per year for the whole sample, (column 1), for academics who have been involved in some kind of collaborative activity at least once during their career (column 2), and separate for each channel of knowledge transfer (columns 3 to 5). Academics are assigned to one or more of the columns if they have used the respective channel at least once during their career. 77.6% of the academics in our sample have been involved in knowledge transfer activities at least once during the sample period. They perform above average for all measures and not only attract more non-collaborative funding, but outperform their colleagues also in terms of research output.

Comparing individuals across the two collaboration channels we find some variance. Researchers collaborating through both types of collaboration channels are also those receiving most other external funding. They further outperform their colleagues in publication and patent numbers (2.81 and 0.10). Those researchers that only collaborate through direct interaction with industry perform below average in terms of publications (1.55) but show average patent numbers of 0.09. Researchers only involved in EPSRC sponsored collaborations, on the other hand, receive almost their entire funding from research councils and little funding from more applied sponsors like the UK government departments. They perform above average in terms of publications (2.54), but have a lower number of patents than researchers receiving direct funds from industry (0.07).

These first descriptive statistics suggest that researchers that only receive income from industry directly are those with the least number of publications. Academics in the other two groups perform above average. This indicates that industry collaboration is generally associated to high levels of academic research output, however, the amount received and the collaboration mediator are important.

3.2.2 Econometric Considerations

The central aim of this study is to estimate how research productivity relates to industry collaboration. Specifically it analyses how academic productivity in terms of publications and patents influences collaboration with industry. The effects are measured after controlling for the effect of past collaboration and access to other non-collaborative grants.

Traditionally publications have been associated with academic benefit and hence been considered the foremost goal of research activity. However, increasingly academics are judged also by their ability to raise money through research grants. Specifically in engineering, which is the focus of this study, research grants provide financial aid to applied research, which by definition requires expensive equipment. Unlike in other subject areas, research money also is a key criterion for promotion and salary increases. For example, the University of Strathclyde requires engineering staff to give evidence for grantsmanship. Loughborough University specifically expects external grants of £50,000 per annum for promotions to Senior Lecturer level.

Publications and patents help attract external funding by attracting attention of external parties. Firms have been found to consider academic quality when searching for a research partner (Blumenthal et al., 1996b; Zucker et al., 1998) and additionally patents generate positive externalities by indicating real-world impact (Audretsch et al., 2006). According to Owen-Smith and Powell (2001a) "many inventors reveal that they patent, in part, because they feel it increases their academic visibility and status by reaffirming the novelty and usefulness of their work". They further report that patents can leverage on industry, leading to grants and consulting contracts.

However, while successful grantsmenship is associated with high publication and patent output, the direction of causality is two way. Just as research outputs may help to gain funding, research money enables academics to more productive and hence produce more publications and patents in return. It is therefore necessary to consider a dynamic model that takes into account endogeneity of the research process.

I model receipt of a specific type of funding ((1)direct industry funding, (2) research council funding involving partners from industry, (3) government ministry funding, and (4) research council funding without partners from industry) as a function of the lag of funding from this specific funding agent, lags of funding from other agents, past publications, past patents, department income and seniority. Taking logs on both sides we take the following equation to the data:

$\ln(Fund^f_{it}) = \sum_{f=1}^{4} \beta_{1f} \ln(Fund^f_{it-1}) + \beta_2 \ln(MeanPub_{i,t-1}) + \beta_3 \ln(MeanPat_{i,t-1}) + \gamma_1 x_{it} + \delta_1 w_{it} + \varepsilon_{it}$

with $\varepsilon_{it} = \eta_i + \nu_{it} + \tau_t$ and $f = 1, 2, 3, 4$, where f stands for the four different funding agents considered in this study, i is the cross-sectional unit and t is the time period. . $Fund_{it}^{f}$ is the measure of funds from funding source f received in period t. $MeanPub_{i,t-1}$and $MeanPat_{i,t-1}$indicate the average number of publications and patents in the 3 years prior to receiving the grant. x represents other strictly exogenous covariates, e.g. years and university wealth and departmental funds, and w other endogenous and predetermined variables, e.g. seniority. The error term ε_{it} consists of a time-invariant individual-specific effect η_i, time dummies τ_t and a idiosyncratic disturbance term ν_{it}. All measures are log-transformed to normalise the highly skewed distribution.

Of specific interest to the analysis are parameters β_2 and β_3, which reflect the effect of academic and commercial effort on the propensity to gain funding. Both are endogenous and determined by past funding. In order to control for endogeneity, I use as instruments departmental and university characteristics that are likely to influence the number of patents and publications and lags of the regressors themselves but are unlikely to be correlated with the unobserved factors influencing the dependent variable in the equations above . I describe those instruments in the next section.

3.2.3 Empirical Method

System GMM The model is estimated using system general method of moments (GMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) in order to solve heteroscedasticity and endogeneity. The problem of heteroscedasticity arises as scientific research is affected by individual specific characteristics and systematic differences between individuals. Endogeneity occurs as the regressors are likely be correlated to the unobservable determinants of the equations, the individual specific time-invariant effects, e.g. ability, talent, etc. We observe the latter when collaboration and publications are both linked to experience or reputation and hence are correlated to the time-variant error term. Moreover, we experience reverse causality, as any factor in the analysis can be considered both an input and an output of scientific research (Bonaccorsi and Daraio, 2003). Researchers with publications and patents increase their visibility to attract grants, but grants enable and enhance productivity of research and hence lead to publishable and patentable outputs.

GMM provides methods to solve these problems by first-differencing the equations and using lags of the regressors as instruments. In the final GMM-model funding history, publication and patent outcomes and academic rank are considered endogenous and instrumented for. Lags of these regressors as well as differences of the exogenous regressors are used as instruments. Additionally, differences of measures indicating the number of patents and publications produced at the department level are used as additional instruments.

In order to make the results more consistent and given the low number of T I use System GMM, which adds additional moment conditions in levels and uses differences of endogenous regressors and levels of exogenous regressors as instruments. It further allows adding time-invariant variables as instruments to the level equation. In this analysis, university dummies, university group dummies, subject indicators and RAE quality indicators are added (see Table 10 for an overview) The two-step estimator is utilized for efficiency; standard errors are corrected using Windmeijer correction (Windmeijer, 2005).

3SLS. It is possible that unobserved characteristics influence all the equations and that different types of funding act as complements (Jensen et al., 2010). I therefore additionally estimate the model as a system of simultaneous equations using three-stage least squares (3SLS). 3SLS allows for the idiosyncratic terms (errors) to be correlated and further allows the equations to contain endogenous variables. Additionally to the four structural equations estimated through GMM, I include three equations that estimate the endogenous variables publications, patents and academic rank. As instruments, just as above, I use the number of patents and publications produced by researchers in the department and lags of the dependent variables. Though this method adds to the GMM I am unable to sufficiently control for individual heterogeneity and the endogeneity caused by the dynamic feedback variable.

3.3 Results

I firstly aim to estimate the effect of academic productivity on the amount of funding received through two different channels of industry collaboration. Additionally I report results for two non-collaborative forms of funding for comparison. The results of the dynamic panel data estimations are presented in Table 11. Columns 1 and 2 report estimates separately for each of the two collaboration channels, column 3 presents results for government department funding and column 4 for public and research council funding that does not involve partners from industry. The results of the 3SLS estimation are reported in Table 12.

We observe that direct funding from industry is indeed influenced by existing involvement with industry, indicating that an increase in funding in the previous period also increases future funding. Collaboration variable 2 (column 2), also, is significantly influenced by existing EPSRC grants involving industry, though the effect is smaller. Other types of funding have no significant effect on the propensity to receive funding through either channel. Similar effects are found for non-collaborative funding in columns 3 and 4. There is also an overall strong impact of funding received in the previous years, confirming the general skewedness of funding distribution in academia.

The 3SLS estimates predict a stronger effect of past funding acquisition. This is perhaps caused by the inability of the model to control for individual heterogeneity and endogeneity of the lagged variables. Not only can we observe a stronger effect of past funding from the same agent but also a moderate positive effect of other types of funding, suggesting some complementarities.

Table 11 also presents estimates for the impact of publication and patent numbers on the amount of funding received. The results show that publications have a positive and significant impact on collaborative funding from the research councils. I have taken logs of research funding and most of the regressors and the coefficients can therefore be read as elasticities. A 100% increase in average publication numbers (e.g. from 2 to 4) in the last 3 years increases collaborative funding mediated by the research council by 83%. Direct funding from industry, on the other hand, is not effected by publications but is associated with patenting outcomes. If a researcher were to double the number of patents this would increase the amount of direct funding from industry by 160%. We observe similar effects in the 3SLS estimates in Table 12. The effect of patents is slightly weaker, predicting an increase of 144% in column 1. The effect of publications on research council mediated funding is slightly stronger with 0.892 (compared to 0.832 in the GMM).

Grants from research councils and other public agents that do not involve partners from industry are also positively affected by the number of publications. The effect is much stronger than for collaborative funds and increases public funding at a rate of 2.55.

Funding from mission oriented government departments is not effected by research outputs but seems to be explained by other, unobserved factors. This is supported by the results of the 3SLS estimation. They additionally show that the explanatory power of the model is weakest for government ministry support ($R^2$of 8.7% compared to 13.5% to 17.5% of the other funding variables). The effects for non-collaborative research council funding in the 3SLS are rather surprising, however. The positive impact of publications is much weaker than in the GMM specification but still stronger than the results for other types of funding. Table 12 further reports a strong positive effect of patenting for column 4. Possibly the instruments that could be considered in the 3SLS specification were not sufficient in explaining patent numbers.

Academic rank does not seem to have any significant influence on the receipt of funding for any of the funding variables specified in the GMM estimates. In the 3SLS I find a positive effect of professor (and partly reader) rank for funding from industry and the research councils. Government funding again is not effected by any of the individual characteristics.

Funding available to the department also has no significant impact on the receipt of external funding. The activities of other members of the department seem to play a minor role in personal grant acquisition. There is a positive effect of university wealth on funding specifically from industry and mission oriented government agents.

Finally, we should also note that the effect of regional business expenditure on R&D has a negative impact on direct funding from industry.

3.4 Discussion

This paper investigated the impact of research output measures on different collaborative activities with industry. A unique database of 479 academic engineers was utilised to investigate the effect on two different channels of industry collaboration: (1) joint research financed by the industrial partners, and (2) joint research sponsored by a publicly-funded agency. These results were compared to determinants of funding from two other agents: (1) the mission oriented government departments, and (2) funding from publicly funded agencies that do not involve partners from industry.

I find that publication numbers have a positive impact on the receipt of research council sponsored collaborative funds while they do not have any significant effect on direct funds from industry. Patent numbers, on the other hand, help increase direct industry funding. These results indicate that indeed there are some important differences between the two channels of industry collaboration.

Collaborations sponsored through research council funding are subject to peer review where publication numbers inform the decision of the funding agent. Industry partners often take on a passive role (Perkmann and Walsh, 2009). This is not the case for direct involvement with industry. Though Zucker et al. (1998) argues that firms consider academic quality, and first findings by Thursby and Thursby (2010) on US data find a positive correlation, this is not supported by my results. Changes in publication behaviour do not affect a researcher's propensity to gain or accept industry funding.

The positive effect of patents on direct funding from industry suggests that patents could indeed help to leverage on industry as previously suggested in interviews conducted by Owen-Smith and Powell (2001a). Following the interpretation of Thursby and Thursby (2010) one could further conclude that researchers that signal commercial interest are also more drawn towards application oriented research and direct industry funding. Whether patenting researchers are more attractive to firms or whether they are simply more likely to accept offers made by firms, my findings indicate a strong link between commercialisation and industry involvement.

To take the discussion further, the positive effect of publications on research council sponsored collaboration might suggest that academics involved in scientific research and producing a large number of publications are more likely to choose collaborations with a passive industry partner. This could be supportive of hypotheses by Bercovitz and Feldman (2008) and Tartari et al. (2010) that suggest that some researchers engage in partnerships purely for symbolic reasons to conform to the requirements of the university or of the funding agent itself.

Comparing the results for joint projects to other forms of external support, my analysis reveals that the most able academics gain funding from research councils that does not involve any kind of partners from industry. This again is supportive of symbolic partnerships assumed as a bargaining tool by researchers that are not considered the most able.

I also find that funding from government ministries cannot be explained through academic research outputs. This partly confirms findings by Goldfarb (2008) for researchers repeatedly sponsored by NASA. Mission driven government funding goes to researchers, who produce results of moderate academic value but which perhaps is of high value to the sponsor. My estimates suggest that other factors may explain financial contribution of the government, e.g. existing links to specific research labs.

These additional observations show that academics least driven by traditional academic values are those engaging in projects funded by industry directly but also such sponsored by ministerial government departments. Applied funding agents like industry and government are not involved in partnerships with top researchers (at least not exclusively), perhaps because publication stars are able to gain funding from public agencies (which they can use to their liking) and do not need to fall back on alternative modes of funding. Alternatively, while funding from the UK research councils is strongly correlated with scientific productivity (whether it involves industry or not), direct collaboration with industry and other applied funding agents may require very different skills or circumstances (Owen-Smith and Powell, 2001a).

However, there is also some evidence that the recent changes in funding allocation through the research councils and the push towards more research serving societal needs has had an impact on researchers' grantsmenship. The positive effect of publications is less strong for research council funding involving industry than for such not involving firm partners, suggesting that researchers producing work of medium quality are using the applied partner to bargain research money from the councils.

Results from the department level and regional control variables show that university wealth helps to predict the amount of individual funding and that regional business R&D expenditure correlates negatively with funding from applied agents. The effect of university wealth indicates that initial non-competitive funding is very important to a researcher's funding acquisition process especially for attracting applied funding agents. The negative effect of regional business investment in R&D might hint at the importance of universities in regions with small companies that only have small internal research facilities.

I further give some evidence that even though researchers receive funding through more than one channel there is no strong evidence for substitution or complementary effects when funding is received. The result of the simultaneous regressions is indeed very similar to the results of the separate models.

3.5 Conclusions

There are different scenarios that may explain my results and reflect the intention of the funding agent and the intention of the academic. I give two examples to give possible explanations for the observed trends.

Firstly, funding allocation by the research councils is done through peer review and hence based on the scientific publications of the researcher. It is therefore not surprising that I find a strong link between the two. Industry and government ministries may also seek to work with the most able researchers, however, there is no exclusivity and their decision is not based entirely on research outputs in terms of publications but perhaps on technical reports, products and availability of technical equipment in the university.

Focussing on the intention of the academic, one could argue that academics find research council grants better suited to their needs as they help to support their core research interests. Projects offered by industry or government ministries may instead be application oriented and not very attractive to the most able researchers. More commerce oriented researchers may be attracted to application oriented research projects offered by industry.

Secondly, due to the increased pressure to work with industry, researchers that are less committed to knowledge transfer may engage in partnerships mediated by the research council for symbolic reasons to conform to the requirements of either their university or the research council itself. Researchers with a less convincing publication record may decide to work with industry on research council sponsored projects to increase their chances of financial support. Similarly, science oriented researchers may engage in research council sponsored collaborations as opposed to industry sponsored projects to conform to the requirements of the university, again suggesting symbolic conformance.

In terms of policy implications I conclude that, if the policy maker seeks to support the most able researchers then it is essential to offer continuous financial support through research council grants but also through initial non-competitive funds that are key for building a basis for research competition. Many potential partners approach universities to gain access to specialised equipment that could not exist without such non-competitive grants. The push towards industry involvement is contra productive as it forces researchers into symbolic partnerships.

If the policy maker seeks to establish new sources for research funding then the commercial orientation of researchers should be encouraged further. A collaborative grant offered by the research councils might attract researchers for symbolic reasons and this method of evaluation should be avoided.

Finally, this paper has shed a light on the determinants of industry collaboration as they are gaining importance in the evaluation of academics. Judging from my results, to account for industry collaboration in promotion decisions could indeed change the face of science, as it is not the most able researchers but researchers producing results of little scientific impact that receive industry support. The results hint that academics might engage in purely symbolic partnerships that might counter their scientific efforts. Whether academics change their research behaviour or nor, the results of this paper spark serious concerns about the attempt to consider industry partnerships in promotion and funding allocation.

This paper can only be a first step in the analysis of industry collaboration. I was able to consider two channels of collaboration, both of which were expected to support research projects. The results may indeed be very different for collaborations that are not aimed at fostering research. Academics involved in consulting or staff exchanges may exhibit very different publication and patenting profiles. Further, some of the long-term effect may differ from the short-term effects reported here, particularly in relation to complementarities and substitution between different channels of collaboration. Future research should therefore attempt to collect longer panels and to find measures for other types of collaborations.

This paper made a strong argument in describing publicly funded collaborations as symbolic partnerships. In order to interpret the results more conclusively it would be necessary to establish the role of external partners in collaborative research council sponsored projects, a very challenging task for future research.

Table 7: List of universities.

University Name	No. of Academics in Sample
University of Cambridge	88
University of Durham	13
University of Glasgow	52
University of Lancaster	9
University of Leicester	22
Loughborough University	101
University of Reading	10
University of Sheffield	67
University of Strathclyde	81
University of Swansea	36
Total	479

Table 8: Descriptive statistics.

Number of	Mean	SD	Min	Max
Industry sponsored Collaboration	21352	(159741)	0	5099309
EPSRC sponsored Collaboration	77876	(412865)	0	13400000
Government Funds	9258	(61573)	0	2064353
Research Council & Charity Funds	116089	(827740)	0	38400000
Publications	2.190	(3.067)	0	27
Patents	0.079	(0.368)	0	9

Table 9: Descriptive statistics and ANOVA for different types of collaboration.

Number of	**All**	**Collaboration**		**ANOVA**	**Collaboration Channel**			**ANOVA**
	Sample Mean	Non-Collaborators	Collaborators	F	Industry sponsored	EPSRC sponsored	Using both	F
Industry sponsored Collaboration	21352	0	27408	28.81***	19320	0	44279	26.97***
	(159741)	(0)	(180528)		(75154)	(0)	(237384)	
EPSRC sponsored Collaboration	77876	0	99965	57.66***	0	98868	125916	18.34***
	(412865)	(0)	(465412)		(0)	(493057)	(504116)	
Government Funds	9258	914	11624	29.61***	9670	3426	16552	15.83***
	(61573)	(10529)	(69354)		(46164)	(28279)	(87170)	
Research Council & Charity Funds	116089	20629	143165	21.42***	43701	138540	170896	4.63***
	(827740)	(83978)	(934996)		(130458)	(1149690)	(920267)	
Publications	2.190	0.911	2.553	293.59***	1.555	2.541	2.813	37.18***
	(3.067)	(1.604)	(3.278)		(2.069)	(3.442)	(3.389)	
Patents	0.079	0.031	0.092	26.74***	0.093	0.071	0.103	2.85*
	(0.368)	(0.208)	(0.402)		(0.485)	(0.384)	(0.387)	
Number of Academics	479	107	372		56	119	215	

Standard Deviations in parantheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Variables and instruments used in the regressions.

Regression Variables	Description	GMM Regression	GMM Lags and/or differences used as Instruments	3SLS Regression	3SLS Used as Instruments
ln(Direct funding from Industry)$_t$	Log of amount of funding from industry received in t	x	gmm style	x	
ln(EPSRC sponsored collaboration)$_t$	Log of amount of funding from EPSRC involving industry received in t	x	gmm style	x	
ln(Government ministry funding)$_t$	Log of amount of funding from government ministries received in t	x	gmm style	x	
ln(Public and EPSRC funding)$_t$	Log of amount of funding from public agents (e.g. research councils) received in t	x	gmm style	x	
ln(publications)$_{t-1}$	Log of Average number of articles published by individual i in the 3 years prior to t	x	gmm style	x	
ln(patents)$_{t-1}$	Log of Average number of patents filed by individual i in the 3 years prior to t	x	gmm style	x	
Lecturer$_t$	ommitted category	x	gmm style	x	
Senior Lecturer$_t$	Zero-one dummy if Senior Lecturer	x	gmm style	x	
Reader$_t$	Zero-one dummy if Reader	x	gmm style	x	
Professor$_t$	Zero-one dummy if Professor	x	gmm style	x	
ln(department research orientation)$_{t-1}$	Average number of PhD degrees awarded by individual i's department in the 3 years prior to t	x	lvl & dif	x	
ln(department funding)$_{t-1}$	Log of average amount of funding received by individual i's department in last 3 years	x	lvl & dif	x	
ln(university income)$_{t-1}$	Log of average amount of funding received by individual i's department in last 3 years	x	lvl & dif	x	
ln(department publications)$_{t-1}$	Log of average number of patents filed by researchers in individual i's department in last 3 year		lvl & dif		x
ln(department patents)$_{t-1}$	Log of average number of publications published by researchers in individual i's department in last 3 year		lvl & dif		x
RAE 2001 ranking$_t$	Zero-one dummies for different RAE ranking		lvl	x	
Department/Subject dummies$_t$	Zero-one dummies for different departments		lvl		
Technical university$_t$	Zero-one dummy if university developed from a technical school		lvl	x	
Russell Group university$_t$	Russell Group		lvl	x	
Other university$_t$	Zero-one dummy if other university		lvl	x	
University dummies$_t$	Univeristy fixed effect		lvl		
regional business R&D$_t$	Amount of regional business investment in R&D	x	lvl & dif	x	
regional gross value added$_t$	Amount of regional gross value added	x	lvl & dif	x	
Year dummies	Zero-one dummy if a professor filed a patent in last 3 years	x	dif	x	

Table 11: GMM regression. Impact of publications and patents on collaboration and funding propensity.

VARIABLES	(1) ln(Direct funding from Industry)	(2) ln(EPSRC sponsored collaboration)	(3) ln(Government ministry funding)	(4) ln(Public and EPSRC funding)
ln(Direct funding from Industry)$_{t-1}$	0.136***	-0.0129	0.00575	-0.00329
	(0.0299)	(0.0225)	(0.0181)	(0.0364)
ln(EPSRC sponsored collaboration)$_{t-1}$	0.000135	0.0793***	0.00798	0.0133
	(0.0154)	(0.0271)	(0.00947)	(0.0222)
ln(Government ministry funding)$_{t-1}$	0.0465	0.0381	0.0758**	-0.0196
	(0.0295)	(0.0315)	(0.0375)	(0.0341)
ln(Public and EPSRC funding)$_{t-1}$	0.00228	0.0213	-0.00632	0.0564**
	(0.0129)	(0.0184)	(0.00878)	(0.0247)
ln(publications)$_{t-1}$	0.287	0.832***	0.142	2.554***
	(0.200)	(0.282)	(0.123)	(0.345)
ln(patents)$_{t-1}$	1.610*	-0.875	-0.370	-0.487
	(0.836)	(0.708)	(0.412)	(0.899)
Lecturer$_t$	ommitted	ommitted	ommitted	ommitted
Senior Lecturer$_t$	-0.428*	-0.207	-0.282	-0.472
	(0.251)	(0.393)	(0.194)	(0.432)
Reader$_t$	0.517	0.398	-0.0213	0.170
	(0.444)	(0.533)	(0.250)	(0.657)
Professor$_t$	0.625	0.765	0.250	0.193
	(0.465)	(0.538)	(0.314)	(0.674)
ln(department research orientation)$_{t-1}$	3.239*	-2.290	1.337	2.313
	(1.825)	(2.986)	(1.403)	(3.377)
ln(department funding)$_{t-1}$	0.0676	0.0705	-0.0105	-0.268
	(0.129)	(0.206)	(0.0998)	(0.252)
ln(university income)$_{t-1}$	1.484***	0.335	0.356**	0.963**
	(0.237)	(0.311)	(0.176)	(0.406)
regional business R&D$_t$	-0.280**	0.145	-0.123*	-0.155
	(0.121)	(0.135)	(0.0731)	(0.157)
regional gross value added$_t$	0.567	-0.341	0.0731	0.251
	(0.381)	(0.465)	(0.261)	(0.563)
Constant	-15.63***	5.268	-4.870	-10.05
	(5.276)	(8.076)	(3.912)	(9.261)
Observations	4220	4220	4220	4220
Number of id	479	479	479	479
Number of Instruments	263	263	263	263
AR(2) test z (p-value)	0.4265	0.2547	0.5947	0.2066
Sargan test p-value	0.1609	0.0736	0.0704	0.1832

Robust standard errors in parentheses

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

Table 12: 3SLS regression. Impact of publications and patents on collaboration and funding propensity.

VARIABLES	(1) ln(Direct funding from Industry)	(2) ln(EPSRC sponsored collaboration)	(3) ln(Government ministry funding)	(4) ln(Public and EPSRC funding)
ln(Direct funding from Industry)$_{t-1}$	0.288***	0.0295	0.0287**	0.0229
	(0.0157)	(0.0198)	(0.0123)	(0.0215)
ln(EPSRC sponsored collaboration)$_{t-1}$	0.00109	0.206***	0.0213**	0.0367**
	(0.0123)	(0.0155)	(0.00966)	(0.0168)
ln(Government ministry funding)$_{t-1}$	0.0511**	0.0302	0.244***	0.0620**
	(0.0205)	(0.0258)	(0.0161)	(0.0280)
ln(Public and EPSRC funding)$_{t-1}$	0.0153	0.0601***	0.00142	0.197***
	(0.0116)	(0.0146)	(0.00910)	(0.0159)
ln(publications)$_{t-1}$	0.0900	0.892***	0.0163	1.472***
	(0.125)	(0.157)	(0.0978)	(0.170)
ln(patents)$_{t-1}$	1.443***	-0.446	0.494	1.194**
	(0.424)	(0.534)	(0.333)	(0.580)
Lecturer$_t$	ommitted	ommitted	ommitted	ommitted
Senior Lecturer$_t$	0.125	0.328	-0.0336	0.304
	(0.164)	(0.207)	(0.129)	(0.225)
Reader$_t$	0.556***	0.301	0.0965	0.522*
	(0.213)	(0.268)	(0.167)	(0.291)
Professor$_t$	0.908***	0.776***	0.214	1.013***
	(0.188)	(0.238)	(0.148)	(0.258)
ln(department research orientation)$_{t-1}$	0.0741	0.0507	-0.122	0.0945
	(0.156)	(0.197)	(0.123)	(0.214)
ln(department funding)$_{t-1}$	3.736*	-1.226	2.418	0.455
	(1.959)	(2.470)	(1.538)	(2.681)
ln(university income)$_{t-1}$	1.527***	-0.393	0.548**	0.572
	(0.308)	(0.388)	(0.242)	(0.421)
regional business R&D$_t$	-0.340***	0.318***	-0.127*	-0.219*
	(0.0860)	(0.108)	(0.0676)	(0.118)
regional gross value added$_t$	0.0171	-0.634*	0.00125	0.0374
	(0.294)	(0.370)	(0.231)	(0.402)
Russell Group university$_t$	ommitted	ommitted	ommitted	ommitted
Technical university$_t$	-1.03	0.346*	-0.239*	-0.414*
	(0.166)	(0.210)	(0.131)	(0.228)
Other university$_t$	-0.508**	0.614**	-0.200	0.646**
	(0.223)	(0.281)	(0.175)	(0.305)
RAE Ranking$_t$	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Constant	-16.70***	4.857	-8.489	-3.777
	(5.443)	(6.863)	(4.274)	(7.449)
R-square	0.175	0.135	0.087	0.151
Observations	4220	4220	4220	4220
Number of idcode	479	479	479	479

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

CHAPTER IV

ACADEMIC PATENTING: OPPORTUNITY, SUPPORT OR ATTITUDE?

4.1 Introduction

Universities have traditionally been an important source for knowledge creation and economic growth. They support industrial innovation through solving fundamental research problems (Aghion et al., 2008; Gibbons and Johnson, 1974; Nelson, 1986) and contribute directly through licensing of inventions resulting from their research (e.g. Henderson et al., 1998; Thursby and Kemp, 2002). Since the 1980s universities have become increasingly proactive in their commercialisation efforts and the number of academic staff involved in patenting increased dramatically (e.g. Jensen and Thursby, 2001; Siegel et al., 2007; Verspagen, 2006).

Numerous studies have investigated the determinants of academic patenting activity and have found three factors that potentially affect a researcher's propensity to patent. Firstly, many papers stress the importance of patenting support provided through the commercialisation unit of the university and through financial incentives (e.g. Foltz et al., 2003; Lach and Schankerman, 2008; Thursby and Kemp, 2002; Thursby et al. 2009). A second body of literature has focussed on the patenting opportunities of individual researchers by measuring their scientific activity (e.g. Azoulay et al., 2007; Stephan et al. 2007). Some recent papers have further highlighted that the influence of peers on researcher's attitudes towards commercialisation (patenting attitude) is one of the main factors for successful patenting (Bercovitz and Feldman, 2008; Stuart and Ding, 2006).

This paper aims to contribute to the latter stream of patenting literature by investigating the influence of partners from industry on patenting. Interviews with engineers conducted by Agrawal and Henderson (2002) suggest that interactions with industry can steer academics towards commercialisation. This points to the possibility that industry partners influence a researcher's attitude towards patenting. I additionally consider in this analysis factors of patenting support e.g. support provided by the university as well as non-collaborative financial stimuli, and factors indicating the scientific activity of academics (patenting opportunities), e.g. publications and access to financial resources.

The inclusion of funding in the analysis of a researcher's patenting propensity, could moreover challenge the existing evidence on the impact of publication numbers on patents, due to the strong correlation between the two. In previous papers I have already shown a strong link between funding and publications and moreover have found no significant effect of patenting on publications (Banal-Estanol et al., 2010; Meissner, 2010). While a large number of studies find a positive impact of publication numbers on a researcher's propensity to patent (Azoulay et al., 2007; Breschi et al., 2005; Calderini et al., 2007; Carayol, 2007; Stephan et al., 2007), in a study by Bercovitz and Feldman (2008), that already controls for some public research funding and a series of peer group factors, this effect is observed to be very small.

This paper uses data from a 12 year panel of 479 engineering academics in the UK, and finds that collaboration with industry is the best predictor of patent numbers. This suggests that industry partners exert a positive effect on a researcher's approach towards patenting. I further find that researchers producing a large number of publications have more possibilities to produce patentable research, however, not to the extent suggested by other papers. I find evidence to refine the effect of publications, specifically, that high impact research is better equipped to produce novelties that can be turned into patents. Additionally I give evidence that TTO support can help to open up a path towards commercialisation for academics, but has no significant impact on the number of patents generated.

The paper is organised as follows: Section 2 reviews existing literature and describes the three different dimensions affecting commercialisation of academic research: opportunity, support and attitude, at the individual and institutional level. In section 3 I summarise the data and introduce the empirical model and the methodology, considering the panel structure of the data, the large number of zeroes and endogeneity present. Section 4 presents the results and section 5, finally, discusses and concludes.

4.2 Patenting: Opportunity, Support and Attitude

Previous research has shown that university researchers differ significantly in their commercial activities (Louis et al., 1989). Researchers differ in their opportunities to patent as well as in their attitudes towards the commercialisation of research. Moreover, do they receive different levels of support for patenting. This section discusses the most important individual and institutional factors affecting an academic's patenting propensity.

4.2.1 Individual Factors of Patenting

A first important individual factor recognised by economic literature is scientific excellence. It has repeatedly been argued that patents could potentially result from any applied research project that also generates publications. Agrawal and Henderson (2002), for instance, cites an engineering faculty member at MIT, saying that "most patentable research is also publishable" (Agrawal and Henderson, 2002, p. 58). Indeed both activities can be complementary as the effort associated with and nature of research do not differ (Dasgupta and David, 1994). Murray and Stern (2007), for example, find that 50% of a sample of articles in Nature Biotechnology are accompanied by a patent. Hence, academics with the ability to successfully conduct scientific research also have the assets to produce commercial outputs. Accordingly, research by Zucker et al. (1998) suggests that researchers with an excellent publication record are also most likely to patent their research (see also Di Gregorio and Shane, 2003; Louis et al., 2001; Zucker and Darby, 1996). Recent empirical work confirms the positive impact of publication numbers on the propensity to patent (Bercovitz and Feldman, 2008; Carayol, 2007; Stephan et al., 2007; Thursby and Thursby, 2007). Studies by Breschi et al. (2005) and Azoulay et al. (2007) using duration models, for example, report a positive correlation between the number of publications and patenting events. It therefore appears that only the most productive researchers in terms of publications have the opportunities to engage in commercial activities. However, Agrawal and Henderson (2002), while controlling for fixed effects, finds no significant correlation between the number of publications and patents for a sample of engineers at MIT and Calderini et al. (2007) finds some evidence for a curve-linear relationship. While most patentable research is also publishable, not all publishable research is patentable. However, publications are a first good indicator for the research activity of an academic.

Additionally to publication numbers, the access to external research funding can be considered an important factor for producing patentable research. Research funding, especially in applied engineering science, is essential to acquire laboratory equipment required for research and allows the employment of research assistants. Accordingly, surveys by Zucker et al. (1998), and Link et al. (2007) indeed find that experience in managing grants adds to more effective patenting. Moreover, the access of funding may support patenting directly through provision of expertise by the funding agent or specific appropriation requirements.

However, not all researchers receiving external grants pursue commercialisation of their research equally and there exists evidence for a very skewed patenting process (Agrawal and Henderson, 2002; Azoulay et al., 2007; Thursby and Thursby, 2007). While scientific experience and funding enable academics to produce and better recognise potentially patentable research, the academic may simply not ascribe high value to commercial activities. Traditionalists amongst academic researchers might indeed feel that commercialisation threatens academia and that the two should be distinct (Owen-Smith and Powell, 2001b).

Building on this conflicting evidence, this paper investigates whether industry funding, rather than publications or external grants as such, are responsible for pushing researchers towards commercialisation. Collaboration with industry and other applied sponsors helps overcome the barrier between scientific and commercial activities. Several studies have shown that industry provides funds and ideas for research (Lee, 2000; Mansfield, 1995; Siegel et al., 2003), and may steer them towards commercialisation (Agrawal and Henderson, 2002; Gulbrandsen and Smeby, 2005). Exchanges with the business community and joint research projects may hence help to overcome an intrinsic fear of changes in academia and steer academics towards patenting.

The individual factors described in this section refer to the three different aspects that enable patenting: opportunity, support and attitude. Figure 4 gives an overview over the different dimensions. While scientific publications and access to funding indicate a researcher's opportunity to produce patentable outcome, funding moreover provides the support necessary. Contacts with industry then may impact on a researcher's attitude towards commercialisation.

4.2.2 Institutional Factors of Patenting

Though undoubtedly patenting is prompted primarily by an academic's desire to solve research questions (Levin and Stephan, 1991) it is also affected by the opportunities of the scientific field, the nature of rewards associated with patenting and the support given to the academic (David and Dasgupta, 1994).

The characteristics of the scientific field and industrial relevance of research are important factors in the opportunities for patenting research findings. Firstly, not all areas of research produce patentable outcomes, and other forms of commercial output and intellectual property, such as software and architectural works, may be generated. Secondly, the benefits associated to patenting differ between fields (Owen-Smith and Powell, 2001a).

It has further been shown that the support provided through the university is essential for successful patenting. Since the 1980s most universities in the US and across Europe have established commercialisation units (e.g. Technology Transfer Offices (TTOs)) to better identify commercial opportunities, provide expertise for efficient patenting and to source potential licensees of university inventions. Characteristics of these commercialisation units have indeed been found to positively influence the number of invention disclosures (e.g. Siegel et al., 2003; Thursby and Kemp, 2002). Moreover, the share of licensing revenue positively effects the number of inventions disclosed to the university (e.g. Lach and Schankerman, 2008; Thursby et al., 2009). Thus, activities of the TTO may increase the willingness of academic staff to patent and license, encouraging strategic choices in the dissemination of research (Geuna and Nesta, 2006; Thursby and Thursby, 2002).

Although these findings suggest university policies and culture to have a strong impact on commercialisation activities, Louis et al. (1989) in a survey of US life-science researchers and Bercovitz and Feldman (2008) analysing the disclosure activity of researchers at two medical schools, find socialisation and peer effects to be better predictors. Bercovitz and Feldman, (2008) finds the patenting activity of researchers of similar rank in the same department to positively affect an academic's attitude towards patenting. Several other papers also report evidence that the proportion of inventors at the university level and in the department has a positive effect on patenting (Breschi et al., 2005; Louis et al., 1989).

The institutional factors again reflect the three different aspects that enable commercialisation of research (Figure 4): opportunities provided by the scientific field, support provided by the TTO and attitude shaped by the activities of peers.

To summarize, literature has identified several factors influencing academic patenting: (1) indicating the opportunity for commercial research, (2) the support for successful patenting, and (3) factors shaping a researcher's attitude towards commercialisation.

4.3 Data and Methods

4.3.1 Data and Descriptive Statistics

Longitudinal data on academic, commercial and collaborative histories of 479 tenured academics from 10 UK universities for the period 1996 to 2007 is used to analyse a researcher's propensity to patent (for a list of universities see Table 13). The data for this analysis comes from a larger dataset collected at City University in 2008 that comprises information on more than 4000 engineering academics from 40 universities over a 22 year period (see Banal-Estanol et al., 2010). Initially, researchers were identified using staff registers in academic calendars, which provided the basis for collecting individual information from the Internet, and researchers' publication and patent histories from existing databases. 10 universities additionally provided information on external funding received from industry, government and public bodies for the period 1996 to 2007. Only academics that remained in the sample for the first 10 years (1996 to 2005) were considered to allow for a sufficiently long observation period. Table 13 gives an overview over the average size of the engineering schools at the 10 universities and shows the distribution of the sample across universities. The sample includes approximately 50% of the engineering staff at the 10 schools. For three of the small universities this share is much lower, indicating that more academics stay for just a short period of time before perhaps moving on to more established engineering departments.

In this section I give a detailed overview over the collected data. Descriptive statistics for some key variables are presented in Table 14. Table 15 lists the variables used in the regression.

Patents. For each academic in the dataset, patents stating her as an inventor were collected from esp@cenet, developed by the European Patent Office (EPO). The web interface allows searches for patents filed with the EPO but also those filed with the UK Intellectual Property Office (UKIPO) and other national patent offices. I consider here all patents that state the researcher as an inventor and hence not only patents filed by the university but also those assigned to third parties, including industry. Data construction required a manual search in the inventors database to identify those entries where the identity of the academic was certain. This was done by comparing addresses, titles and technology classes for all patents potentially attributable to each researcher.[1] As each invention can lead to multiple patents, I additionally verified each entry with the Derwent World Patents Index (DWPI) that contains information grouped around a base patent, thus enabling me to uniquely identify the original invention and avoid multiple counts.

I collected all patents ever granted to each researcher and recorded the year of priority which represents the date closest to invention. The oldest collected patent dates from 1964, indicating that patenting is not a new phenomenon in universities in the UK. In total 196 inventors were granted 727 original patents. 149 patents were only issued at national patent offices (mostly UKIPO), 578 were registered at the EPO or WIPO (World Intellectual Property Office). 156 of the 196 academic inventors filed patents during the observation period 1996 to 2007. A third of the patenting researchers filed only one patent during their entire career to date. 40.6% of patents are assigned to a company and only 37.0% to universities. This confirms the importance of considering non-university patents when analysing academic patenting in Europe (Geuna and Nesta, 2006).

The majority of researchers (67.43%) does not patent during the observation period. Even among those academics who patent during the 12 year period, 69 (more than 44%) do not file more than one patent. Hence, the average number of patents in our sample is low with approximately 0.08 patents per academic per year (see Table 14) and a share of zero observations of 93.88%. This shows that patenting is not widely spread amongst university scientists even in applied engineering sciences.

[1] 41 academics with common names had to be removed from the data as it was not possible to uniquely identify their patents.

Funding and Collaboration. Funding information for each academic was provided by the research offices of the 10 universities. They included names of principal investigators, funding periods, funding amounts and the natures of sponsoring agents. Researchers receive external funding from five different agents: (1) UK research councils, (2) industry, (3) government ministries (excluding research councils), (4) EU, and (5) not-for profit organisations. Academics receive half of their funding from the UK research councils, amounting to an average of 19,821 GBP per academic per year (see Table 14). An average of 8,626 GBP, 21% of funding, is received from industry sponsors. The other three funding agents contribute less than 10% each.

To account for the length of a grant and to avoid focussing all the funding on the start of a project, the grant value was divided by the length of the grant period and equally distributed across years except for the first and last year of a project, which were assigned half-year values as they do not represent full years. More than 60% of external funding extended over a period of one to three years, and a small number were long-term grants. Less than 1.5% of grants extended over six years or more. I generate 3-year moving averages of the different grant variables to account for the length of the research projects and to allow for a long term effect of external income on commercial research activity.

To account for patenting opportunities I create an indicator variable that takes the value one if a researcher receives less than 2000 GBP annually over a 3 year period. Such low amounts of funding are not targeted towards research but are perhaps providing travel or conference assistance. Approximately 45% of observations take the value 1.

To estimate the impact of industry funding on patenting propensity I calculate the share of funding from industry received over the previous 3 years. On average, 21% of funding comes from industry with some researchers receiving funding exclusively from private sponsors. The correlation coefficients in Table 16 show that industry funding correlates stronger with patenting than with publications though both coefficients are very small. Funding in general correlates stronger with publication numbers than with patenting. This might indicate that indeed considering funding in the analysis of patenting propensity may diminish the effect of publications.

Publications. Information on articles published during the observation period was extracted from the ISI Science Citation Index (SCI) for each academic in the sample. Entries were matched using authors' names, affiliations and article titles. The SCI includes journals based on a selection and reviewing process and is hence biased towards work of scientific importance. These journals represent the most important journals in their field and will serve as a measure for academic research output in this analysis. The average number of publications is approximately two articles, though we can observe large heterogeneity in publication numbers with the maximum number in one year being 27 articles for one academic (see Table 14). Additionally, to account for the quality of publications I consider their average impact. I employ the ISI Journal Impact Factor (JIF), a measure for the relative quality of a journal in which an article is published based on the number of citations it received over a 3 year period. Though not a direct measure for the quality of a paper, it reflects its importance attributed by peer-review and presents a good indicator for research impact. The average JIF for publications in my sample ranges from zero to 27.36, the mean value is 0.997 (see Table 14).

As patenting is expected to occur for very productive researchers that publish consistently over a long period, this productivity is measured using moving 3-year averages of publications. Alternatively, researchers that publish consistently in high impact journals might have many more opportunities to patent. I therefore measure the impact as the average JIF of a researcher's publications during the past 3 years. Table 16 shows that both measures are mildly correlated but that funding correlates stronger with publication numbers than with the average impact (though both coefficients are very small). I therefore expect funding to diminish the effect of publication numbers rather than that of publication quality.

I create an indicator variable of publishing activity that takes the value one if an academic publishes less than 1 article annually over a 3 year period, which represents just below 40% of the sample. This indicator should help to identify those researchers that have no opportunities for patenting.

Institutional Factors. Academics were grouped into engineering departments according to Research Assessment Exercise (RAE) categories. Five subject dummies were created, Electrical and Electronic engineering (107 academics), General engineering (118 academics), Mechanical engineering (117 academics), Chemical engineering (64 academics) and Civil engineering (73 academics). Table 17 shows the distribution of inventors and patent observations across the 5 fields of engineering. These first statistics show that patenting is most widely spread in Electrical and Electronic Engineering as well as Chemical Engineering. These two fields also show the largest average number of publications, indicating a strong link between both types of research output. Civil engineers generate the least number of patents and publications. They also show lower levels of funding and industry involvement. Funding levels, however, are lowest for researchers in Chemical engineering. There hence are significant differences in the research behaviour of researchers in different fields of engineering. Funding, publications and patent levels seem to be linked within each field, the only exception being Chemical engineering that shows a large number of publications and patents despite low levels of funding.

To control for differences across these engineering departments in terms of size, research activity, wealth and quality, I use data from the 2001 and 2008 RAE submissions. For each department I gather information on external research income reported to the RAE and calculate the share of income from industry contracts. I further use the number of PhD degrees awarded and RAE quality ratings as measures for department research quality. Additionally, based on information from the full sample of 5000 academics, I retrieve the number of active members of staff in the same department.

As proxies for peer effect I use the number of academic inventors in the same department and an indicator taking the value one if these included a senior member of staff, based on information from the large dataset. Again, to account for the lag in effects, I use moving averages over 3 years as variables in my analysis.

Further, as mentioned above, studies have found TTO support to have a significant effect on patenting activity in the university. I use the number of TTO staff reported to the Higher Education Business and Community Interaction (HE-BCI) survey in 2006 as a proxy for support provided.

Promotion. I also include a control to account for an academic's recent promotion. Academic rank information was collected from university calendars and indicates whether the researcher has been promoted during the past 3 years. Promotion requirements of the university may effect the type of research done by the academic and a recent promotion may hence allow an alternative research behaviour.

4.3.2 Model and Methodology

As discussed above, previous papers reported that patenting is influenced by publication numbers and external funding and that collaboration with industry may additionally steer researchers towards commercialisation. Further, research field, department and university characteristics and peer activity may have an impact on a researcher's patenting propensity. It has further been shown that patenting is a highly skewed process and that therefore it is important to consider dynamic feedback mechanisms and individual heterogeneity. All factors are considered in the period $t-1$ to allow for a lag in the effects.

The model I seek to estimate is described by the following equation:

$$Pat_{it} = \beta_0 + \beta_1 PatStock_{it-1} + \beta_2 \ln(PubAvg_{it-1}) + \beta_3 \ln(IndFund_{it-1}) + \beta_4 Prom_{it-1} + \beta_5 PeerPat_{it-1} + \gamma_1 r_{dt-1} + \gamma_2 Field_d + \gamma_3 s_d + \eta_i + \nu_{it} + \tau_t$$

Where Pat_{it} represents the number of patents filed by academic i in year t. $PatStock_{it-1}$ measures a researcher's accumulated patenting stock up to $t-1$, $PubAvg_{it-1}$ is the academic's scientific capital (mean number of articles published during the 3 years prior to t); and $IndFund_{it-1}$ represents the researcher's tangible industry income (share of industry funding during the 3 years prior to t). $Prom_{it-1}$ is the time variant variable indicating a researcher's promotion during the previous 3 years. $PeerPat_{it-1}$ are the variables indicating the patenting activity of researchers in the same department (number of patenting staff and existence of a senior inventor in the last 3 years) and r_{dt-1} are other time variant departmental variables including department size, department income and research activity of department d during the 3 years prior to t. $Field_d$ indicates the scientific field and s_d then represents other department and university specific time invariant characteristics including department quality and university fixed effects. η_i is the individual specific fixed effect, τ_t is the time specific effect and ν_{it} the disturbance term.

The data used in this analysis is characterised by an excessive number of zeroes (more than 90% of observations). Some of these zeroes are expected to be "certain zeroes" (those researchers assumed never to have opportunities for patenting), thus, the number of zeroes may be inflated and non-patenting cannot be explained in the same manner as patent events.

Several methods have been employed to deal with large numbers of zeroes in economic research and the most flexible approach is known as the double-hurdle or two-step model (Cragg, 1971). This model makes a distinction between e.g. un-patentable research and not patenting patentable research. Cragg (1971, p. 831) described this process as follows: "First a positive amount has to be desired. Second, favourable circumstances have to arise for the positive desire to be carried out". Accordingly, zero patenting may mean either non-participation in patentable research or non patenting due to factors such as patenting support, individual attitudes or research opportunity. There are hence two hurdles or steps in this model that a researcher must pass before patents are filed: produce potentially patentable research and actually patent.

In this study, the zero-inflated negative binomial (ZINB) model is chosen to estimate patenting. It represents a mixing specification which adds extra weight to the probability of observing a zero. It can incorporate the framework of a double-hurdle or two-step model by distinguishing between two different zero outcomes. It further allows for potential overdispersion of patenting frequency, which is indicated by $Var(Pat_{it}) >> E[Pat_{it}]$, and for unobservable heterogeneity (Carayol, 2007; Greene, 1994). Zero inflated count data models have commonly been used to model traffic accidents and health treatments, and have increasingly become popular in the analysis of innovation, including academic patenting (e.g. Carayol, 2007; Franzoni et al., 2009; Stephan et al., 2007). The approach and the two hurdles are described in detail below.

Negative Binomial Distribution with Zero Inflation. Patent production is assumed to result from two different regimes underlying scientific research: (1) the engagement in potentially patentable research, and (2) the decision on how many patents to produce, illustrated in Figure 5.

The first process relates to an academic's research effort and orientation. An academic can decide to abstain from research and focus her efforts on teaching and administrative tasks. If she decides to conduct research she can devote different levels of effort to research activity, where active research can potentially lead to a patent. The probability that an academic's work does not lead to a patentable discovery (that a researcher belongs to the "certain zero" group) can then be represented by the zero-inflation parameter p. This can be interpreted as a splitting mechanism that divides researchers into non-patenters, with probability p, and potential patenters, with probability $1 - p$. p is determined by covariates w_{it} including measures for research activity (indicators for external funding and publications in the 3 years prior to t), for opportunities of the scientific filed (engineering sub-fields) and for promotion requirements (promotion indicator). The first-hurdle equation then is:

$\Pr(patentable_{it} = 0|w_{it}) = p = F(\gamma\prime w_{it})$

where $patentable_{it}$ can be interpreted as a researcher's involvement in patentable research. If academic i is not conducting research, $patentable_{it}$ is zero, whereas, if academic i is conducting research, $patentable_{it}$ is one. The function $F(\gamma\prime w_{it})$ can then be modeled as a Logit distribution (Greene, 1994):

$F(\gamma\prime w_{it}) = \exp(\gamma\prime w_{it})/(1 + \exp(\gamma\prime w_{it}))$

The second regime relates to the actual number of patents issued from patentable research for researchers other than those in the "certain zero" group. This includes academics that produce patentable research, but chose not to patent. Reasons for this choice can be a lack of knowledge regarding the patenting process, an inability to recognise commercial opportunities, a lack of administrative support, or individual attitudes that favour open dissemination. These researchers could potentially be steered towards commercialisation, e.g. by an industry sponsor, and are hence not "certain zeroes". As mentioned above, the data is characterised by a large number of zeroes along with a long right tail (prolific inventors). I assume that patenting follows a highly overdispersed Poisson distribution, with small probability of success. To account for overdispersion and the unobserved heterogeneity among academics I assume a negative-binomial distribution, where the probability to patent is determined by covariates x_{it}, which includes all the individual and department level variables of interest to this model. The second hurdle equation is then given by:

$\Pr(Pat^*_{it} = j|x_{it}) = f(j|x_{it})$

where $f(j)$ is the negative binomial probability distribution for Pat^*_{it}.

The two hurdle equations are jointly estimated by means of maximum likelihood. The second hurdle equation is only maximized for observations with $\Pr(patentable_{it} = 0) \neq 1$. The probability to patent is then equal to the probability of the unobserved variable Pat^*_{it} conditional on $patentable_{it}$:

$\Pr(Pat_{it} = j|x_{it}, w_{it}) = patentable_{it} \times Pat^*_{it} = F(\gamma\prime w_{it}) - F(\gamma\prime w_{it})f(j|x_{it}) + f(j|x_{it})$

Thus,

$\Pr(Pat_{it} = 0|x_{it}, w_{it}) = \Pr(patentable_{it} = 0|w_{it}) + \Pr(patentable_{it} = 1|w_{it}, Pat^*_{it} = 0|x_{it}) = p + (1-p)f(0|x_{it})$

$\Pr(Pat_{it} = j|x_{it}) = \Pr(Pat^*_{it} = j|x_{it}) = (1-p)f(j|x_{it})$, $j = 1, 2, ...$

This represents the basic equations of the first ZINB model that I will estimate.

As a second approach I consider an alternative definition of "certain zeroes". In this alternative model, the two regimes are (1) the receipt of support for patenting, and (2) making use of this support conditional on opportunities and attitude. Here the first process relates to the availability of effective patenting support provided by the university or external sponsors. Thus, $patentable_{it}$ is zero if academic i does not receive patenting support, and one if academic i is receiving support.

The second regime again relates to the actual numbers of patents issued from research that receives patenting support. The negative binomial regression then also includes academics that may not actively be involved in research or operate in areas that do not produce patentable outcomes. The results of the negative binomial regression are expected to differ significantly from the first model due to the alternative estimation of "certain zeroes".

Dynamic Feedback and Fixed Effect. It has been discussed above that patenting activity is highly skewed and the majority of patents are produced by a small number of researchers. This difference is unlikely to be explained by observable individual heterogeneity. Instead unobserved differences between individuals have to be an important feature of this analysis as they are most likely correlated with the regressors, potentially creating endogeneity. This endogeneity arises in two ways. Firstly, we are faced with the problem of reverse causality as researchers who patent more may be better able to attract funding from external sources (Jensen and Thursby, 2001; Meissner, 2010). Further, endogeneity may arise through omitted variables as publications, patenting, promotion and grant receipt are correlated to a researcher's skills and effort allocation (see Banal-Estanol et al., 2010).

In order to control for unobserved heterogeneity and control for potential reverse causality I follow Blundell et al. (1995) and estimate a model using the pre-sample values of the dependent variable. I assume that unobserved heterogeneity in my data is mainly caused by the different knowledge stocks with which individuals enter the sample, and that patenting experience should contribute positively to a researcher's propensity to patent. The pre-sample value is given by the number of patents filed by the academic before 1996 whether she was employed by a university or a company at the time.

Theory suggests that research activity and technological innovation are subject to dynamic feedback and it is therefore important to also consider continuous, sample-period dynamics when modeling patent counts (Blundell et al., 1995). To proxy for patenting experience accumulated within the sample period I calculate the depreciated stock of patents filed during the observation period. I use Blundell et al.'s (1995) assumption that previous patents provide knowledge of the patenting process but that the quality of this knowledge decreases over time. The sample period patenting stock is hence defined as:

$PatStock_{it} = Pat_{it-1} + (1 - \delta)PatStock_{it-1}$,

with a depreciation value of $\delta = 30\%$ (following Blundell et al. (1995))

In order to confirm the specifications of the model I carry out several tests. The first step is to test the endogeneity of publications and external funding using Hausman's specification tests. The null-hypotheses of exogeneity is not rejected, suggesting that there is no need for instrumental variable estimations. To test for the selection of the ZINB model I firstly use the dispersion parameter alpha which is significantly different from zero, suggesting that the data is overdispersed and that a negative binomial (NB) model is preferred over a Poisson model. The Vuong test is used to discriminate between NB and ZINB models and suggests that the ZINB model represents an improvement over a NB (Vuong, 1989).

4.4 Results

The results are introduced in Tables 18 and 19. Table 18 present the results using the first model specification for two different publication specifications. Column 1 only considers the publication count variable and column 2 additionally includes the measure for average publication quality. Both specifications are included to investigate whether publication quality replaces or adds to the effect of publication quantity. Table 19 represent the second model specification with an alternative definition of "certain zeroes". All models include year and university dummies. Standard errors are robust and clustered at the individual level. The results show that the fixed effect proxy, pre-sample patent control, is significant and works in the expected direction. Also the stock of patents is highly significant. The predicted number of patents increases by a factor of approximately 1.8 if an academic were to increase the patent stock by one while holding all other variables in the model constant. These first results indicate the dynamic nature of the patenting process and hence the importance of considering dynamic effects in this estimation.

4.4.1 Model 1: Patenting Opportunity as Source of Zero Observations.

Inflation (First Regime) Model. In this first model in Table 18 I am predicting the "certain zeroes" with indicators for low levels of publications and funding during the last 3 years, promotion during the past 3 years and the engineering departments, with chemical engineering being the omitted category. The results show that researchers that on average published less than 1 article and received less than £2000 funding over the last three years are more likely to enter the "certain zero" group. The odds of being a "certain zero" are increased by $\exp(31) = 2.9 \times 10^{13}$ and $\exp(30) = 3.9 \times 10^{12}$ respectively. Hence, while academics generally are at little risk of entering the "certain zero" group (The mean probability of being in the "certain zero" group is 0.180) this probability increases dramatically for academics with low research activity. Also, researchers in the field of mechanical engineering are at greater odds of being a "certain zero" while researcher in Electrical and Electronic Engineering and those in General Engineering are most likely to produce patentable research. Promotion has no significant effect.

The inflation model identifies 472 observations (11% of the sample) as "certain zeroes". Some of the characteristics of these observations are displayed in Table 20. They published less than one article in the past 3 years (mean 0.26), received little to no funding (average of 59 GBP) and are mostly working in Mechanical or Civil Engineering. These 472 observations do not enter the negative binomial (second regime) model.

Negative Binomial (Second Regime) Model. The negative binomial model predicts the number of patents for the remaining 3649 observations. If all the predictor variables in the model are evaluated at zero the expected number of patents would be zero. The mean probability of a count of zero patents is 0.924.

The regression results show that the share of funding received from industry during the last 3 years has a strong positive effect on the predicted number of patents. Receipt of other types of funding also has a positive effect on patent rate, however, the effect is significant at 10% only in the specification in column 2. As the model models the log of expected patents and I have additionally taken logs of most of my explanatory variables to normalise the distributions, the coefficients can be interpreted as elasticities. For illustration let me consider the results reported in column one of Table 18, if the share of industry sponsored research increases by e.g. 10% the predicted number of patents would increase by 7.91%.

Additionally I consider the number of articles published in the last 3 years. I find no significant effect of publications on patenting in the negative binomial part of the regression. Thus, researchers who have produced some patentable research in the previous 3 years, do not have an increased number of patents commensurate with an increase in the number of publications. In column 2 I include the average impact score of publications to the regression. The quality indicator has a positive effect significant at the 5% level on the predicted number of patents. Doubling the average impact score would increase the number of patents by 50%. Researchers with high quality publications thus patent significantly more than their peers with publications in journals of lower average quality.

Promotion has a positive albeit insignificant impact on a researcher's patenting propensity.

Two measures for the patenting activity of researchers in the same department were included to measure the effect of peers. Firstly, I considered the number of academic inventors in the department. I include a quadratic term to account for a potential reverse effect for large number of inventors. Both effects are significant, however the Incidence Rate Ratio (antilog) of the quadratic term is very large in magnitude and turns the effect negative almost instantly. If the number of academic inventors in the department increases by 1, the academic herself will increase her patents at a rate of 0.20. However, if the number of inventors increases by 2 the predicted number of patents decreases at a rate of -1.58. This might indicate some cyclical effects of patenting activity in the department. I therefore additionally include a dummy variable for senior (professor) inventors present in the department. The effect is very strong and positive. The expected number of patents for an academic whose senior colleagues are involved in patenting is 2.66 ($= exp(0.967)$) times that of her peers.

Most other departmental factors have no significant impact. Only the research orientation of the department measured as the average number of PhD degrees awarded during the last three years has a strong positive effect on the expected number of patents. One additional PhD degree awarded by the department increases the number of patents at a rate of 1.03 ($= exp(0.027)$). However, the departments that ranked highest in the RAE 1996 and 2001 respectively seem to be less likely to patent than engineers at other departments. The effect is only significant at the 10% level in the second specification. The impact of external funding received by the department, the number of department staff and the number of TTO staff are insignificant.

4.4.2 Model 2: Patenting Support as Source of Zero Observations.

Inflation (First Regime) Model. In the second model (Table 19) I am predicting "certain zeroes" with indicators for financial support at the individual and departmental level, the size of the department and the number of staff working in the commercialisation unit of the university. The results of the inflation logit suggest that researchers that receive little funding and receive little TTO support are more likely to enter the "certain zero" group. If a researcher was to half the amount of external funding, the odds of being a "certain zero" would increase by 19%. Further if her university was to decrease the number of TTO staff by 1, the odds that she would enter the "certain zero" group would increase by 0.75. The number of staff and department wealth in general have no significant impact on the prediction rates.

The mean probability of being in the "certain zero" group is similar to the previous model with 0.175. The inflation model does not identify a "certain zero" in the sample with a probability of 1 and hence all 4137 observations enter the negative binomial regression.

Negative Binomial (Second Regime) Model. Similar to model 1, the expected number of patents is zero if all predictor variables were evaluated at zero and the mean probability of observing a zero is 0.934.

The regression confirms the positive effect of industry funding on the expected patenting rate and the effect is slightly stronger than in the previous model. Funding from other sources again is not found to have a significant impact on the number of patents.

In this specification I additionally find a positive effect of publishing on the predicted number of patents. This effect is replaced by a strong positive effect of the average quality measure in the specification in column 1. If a researcher increased the number of publications from say 1 to 2 this would increase the number of expected patents by 23%. If instead she didn't publish more but increased the impact factor of the publication, the number of patents would increase by 45%, making quality increase almost twice as efficient as quantity increase.

Overall model 2 shows that for researchers, who receive patenting support through funding and their university TTO, the propensity to patent increases with greater numbers of publications as well as funding from industry. Promotion, again, has no significant impact.

The peer effects are similar to the previous models though slightly weaker. The expected number of patents for an academic whose senior colleagues are involved in patenting is 1.99 (compared to 2.66 earlier). Additionally just like in the previous model the average number of PhD degrees in the department increases patenting at a rate of 1.03. The RAE score is significant at the 10% level and predicts that the number of patents at top ranking departments is 0.579 times lower than at lower ranking departments. The number of TTO staff has no additional impact in the second part of the regression.

Department indicators were included in the model and show that researchers in civil engineering patent less than their colleagues at other engineering departments.

4.5 Discussion and Conclusion

The results presented in this paper represent the first robust evidence of the impact of funding sourcing practices on the propensity and the intensity of patenting at universities. I provide evidence that UK researchers receiving funding from industry are more likely to produce patents, controlling for a variety of individual and departmental characteristics. I take into account the number of "excess zeroes" using a ZINB model, and control for potential endogeneity in the patenting process and individual heterogeneity by including pre-sample values of the dependent variable as regressors to the analysis.

I conclude that the research activity of an academic measured in quantitative terms and the support provided by the department are not conclusive in explaining a researcher's propensity to patent. Indeed, as already argued by e.g. Bercovitz and Feldman (2008) or Owen-Smith and Powell (2001a) the support of pro-commercialisation partners is key in steering researchers towards patenting. I find the effect of an industry partner to be strongest in explaining the number of patents.

This paper represents an attempt to find different individual and department level measures for patenting opportunity, support and attitude in order to estimate their combined effect on the propensity to patent. It discussed the problem of "excess zeroes" and attempted to identify the factors responsible for their occurrence. It presented two models that potentially help identify two groups as "certain zeroes". Firstly, academics that are research inactive (that do not publish and do not receive research funding) or lack the opportunity to patent due to working in academic fields that do not produce patentable research; and secondly, researchers that do not receive patenting support (through TTO's, funding etc.). Results for most of the regressors were robust across both specifications. However, I have shown that the choice of regressors for the inflation regression is important in the interpretation of the models, and that future research should consider carefully the factors used in the first hurdle in a ZINB model.

In the first model I find that researchers respond positively to funding, indicating the importance of financial inputs for the research process. Funding increases the probability of producing patentable research perhaps by providing necessary equipment. This result confirms evidence found by Zucker et al. (1998) in their survey. Publications also increase the propensity to identify commercial opportunities and are an important indicator for determining whether a researcher has assets to patent. However, there is no additional significant effect of publications on patent numbers. This is in line with duration model studies by Breschi et al. (2005) and Azoulay et al. (2007) that report a positive correlation between the number of publications and a patenting event. The most productive researchers in terms of publications are more likely to become inventors, but they are not predicted to file a large number of patents. Instead I find that it is not productive research, but high impact research that is more likely to produce patents. These findings qualify prior studies by confirming that the most productive researchers in terms of publications have many more opportunities to patent their research but that research quality determines whether a patent is filed.

In the main regression of the first model I considered factors that might influence a researcher's attitude towards patenting. I find a positive effect of the share of funding received from industry on the number of patents. This confirms results from survey studies (Gulbrandsen and Smeby, 2005) and anecdotal evidence (Agrawal and Henderson, 2002), indicating a pull effect of industry. Partners from industry perhaps have a strong interest in pushing academics towards commercialisation to recover their research investments. I secondly considered a peer effect by measuring the impact of having a senior inventor in the department and indeed find a positive effect. This confirms the evidence found by Bercovitz and Feldman (2008) that reported a strong effect of peer behaviour on a researcher's behaviour and attitude towards patenting.

The second model considers patenting support as the decisive factor in determining "certain zeroes". The probability to enter the patenting regime is determined by the magnitude of financial resources available to the researcher as well as the support provided by the university's commercialisation unit. Both factors increase the odds of entering the patenting regime. This indicates that TTO support can help to open up a path towards commercialisation for academics. TTO support, however, has no significant impact on the number of patents in the main regression.

The effect of attitudinal factors in the second model is equally as strong as in the first specifications indicating a consistent steering effect of industry funds and peers. The positive effect of publication quality is also confirmed in the second model.

In terms of policy implications I conclude that (1) patentable research benefits substantially from external funding, hence monetary incentives stimulate research for industrial application, (2) internal support provided through a commercialisation unit, e.g. TTO, is critical for recognising patenting opportunities, (3) patentable research arises from productive academics, indicating that some academic research is needed to generate commercial opportunities, however, (4) only high impact research produces novelties that can be turned into patents. Moreover, (5) university-industry collaboration is most effective for transforming knowledge into commercial opportunities. Finally, the opportunities to engage in patentable research may differ between scientific fields even within engineering sciences, policy makers should hence be careful in their expectations of patents.

This paper has added some important evidence to the discussion on university-industry collaboration, but further data and a longer panel is required to draw more robust conclusions. Additionally, it is necessary to collect information for more departments and universities to capture those academics moving between universities. Such academics had to be discounted in this analysis but may represent a very different research and patenting profile.

Due to the small sample size, I was further not able to distinguish between patents owned by university and such owned by company partners. This distinction may help to better understand the effects of industry funding and of commercialisation support provided by the university.

	Opportunity	Support	Attitude
Individual factors	Research Active – Publications Grants	Grants	Industry Links
Institutional factors	Scientific Field – Department	TTO Support University Resources	Peer Behaviour

Figure 4: The aspects of patenting

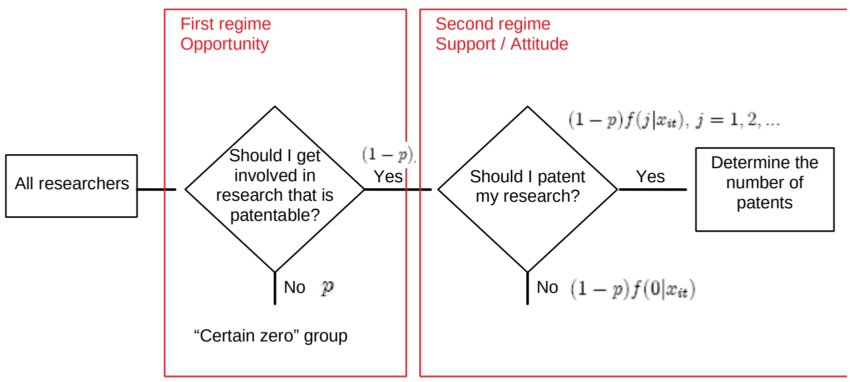

Figure 5: The two regimes of patenting activity

Table 13: List of universities.

University Name	Avg # of Enginnering staff between 1996 and 2007	# Academics in Sample (% of all staff)	% Inventors in Sample
University of Cambridge	158	88 (56%)	47%
University of Durham	33	13 (39%)	38%
University of Glasgow	100	52 (52%)	21%
University of Lancaster	23	9 (39%)	22%
University of Leicester	32	22 (69%)	32%
Loughborough University	191	101 (53%)	37%
University of Reading	39	10 (26%)	60%
University of Sheffield	155	67 (43%)	47%
University of Strathclyde	155	81 (52%)	58%
University of Swansea	70	36 (51%)	28%
Total	**956**	**479 (50%)**	**41%**

Table 14: Descriptive statistics.

	Mean	SD	Min	Max
Individual				
Number of Patents	0.079	(0.368)	0	9
Number of Publications	2.190	(3.067)	0	27
Average Journal Impact Factor	0.996	(1.092)	0	27.36
Funding from Research Councils	19822	(75367)	0	1086509
Funding from Industry	8626	(47942)	0	2005569
Funding from Government Ministries	3916	(17864)	0	300030
Funding from Charities etc.	3513	(31344)	0	826078
Funding from EU	3871	(19271)	0	427209
Institutional				
Number of Department Patents	2.730	(4.144)	0	23
Average Department Funding per PhD	210206	(150327)	0	2944966
Share of Department Industry Funding	0.207	(0.127)	0	1
Number of PhD degrees awared	23.252	(25.298)	0	108
Staff at University TTO	31.552	(14.258)	10	58

Table 15: Definitions of variables used in the regressions.

Regression Variables	Description	Zero Inflation Part Model 1	Zero Inflation Part Model 2
Patent $\#_t$	Number of patents filed by individual *i* in *t*		
Pre-observation Patents	Number of patents filed by individual *i* before 1996		
Patent Stock$_{t-1}$	Depreciated stock of patents filed by individual *i* since 1996 (= pat[t-1]+0.7*patstock[t-1])		
Opportunity			
ln(publications in last 3 years)$_{t-1}$	Log of Average number of articles published by individual *i* in the 3 years prior to *t*		
ln(avg JIF in last 3 years)$_{t-1}$	Log of Average impact of articles published by individual *i* in the 3 years prior to *t*		
Low Publication Activity$_{t-1}$	Zero-one dummy if less than one article published in one year during last 3 years	x	
Low Funding Activity$_{t-1}$	Zero-one dummy if less than 2000 £ were sourced in one year during last 3 years	x	
Chemical Engineering$_t$	omitted category	x	
General Engineering$_t$	Zero-one dummy if General Engineering	x	
Mechanical Engineering$_t$	Zero-one dummy if Mechanical Engineering	x	
Electrical and Electronic Engineering$_t$	Zero-one dummy if Electrical and Electronic Engineering	x	
Civil Engineering$_t$	Zero-one dummy if Civil Engineering	x	
Promotion$_{t-1}$	Zero-one dummy if promoted in the last 3 years	x	
Support			
ln(funding in 3 last years)$_{t-1}$	Log of Average amount of funding received by individual i in last 3 years		x
ln(department funding in 3 last years)$_{t-1}$	Log of average amount of funding received by individual i's department in last 3 years		x
Department staff$_t$	Average number of staff in individual i's department		x
TTO staff$_t$	Number of staff working in dedicated commercialisation unit in 2006		x
Attitude			
ln(share of funding from industry)$_{t-1}$	Log of the average share of funding from industry received by individual i in last 3 years		
Public funding$_{t-1}$	Zero-one dummy if researcher received other types of funding during last 3 years		
Peer patents$_{t-1}$	Average number of patents filed by researchers in individual *i's* department in last 3 year		
Professor inventor$_{t-1}$	Zero-one dummy if a professor filed a patent in last 3 years		
Industry orientation of department$_{t-1}$	Average share of industry funds received by individual *i's* department in last 3 years		
Research orientation of department$_{t-1}$	Average number of PhD degrees awarded by individual *i's* department in the 3 years prior to *t*		
RAE$_t$	Zero-one dummy if department received the highest quality ranking in the 1996 and 2001 RAE		

Table 16: Correlation matrix for individual measures.

	Patent $\#_t$	Publications in last 3 years$_{t-1}$	Avg JIF in last 3 years$_{t-1}$	Funding in 3 last years$_{t-1}$
Publications in last 3 years$_{t-1}$	0.1421			
Avg JIF in last 3 years$_{t-1}$	0.1261	0.4092		
Funding in 3 last years$_{t-1}$	0.1058	0.2693	0.1754	
Share of funding from industry$_{t-1}$	0.0618	0.0118	0.0139	0.0988

Table 17: Descriptive statistics by department (scientific field).

Scientific Field	# Academics	% Inventors	% of Observations with zero patents (4121 obs)	Average Publication Number	Average Funding in GBP	Share of Funding from Industry
Chemical Engineering	64	55%	90%	3.839	17178	24%
General Engineering	118	39%	93%	2.217	59274	27%
Mechanical Engineering	117	35%	95%	1.653	26824	28%
Electrical and Electronic Engineering	107	60%	90%	2.488	55918	24%
Civil Engineering	73	14%	99%	1.093	22407	16%
Total	**415**	**41%**	**93%**	**2.19**	**39428**	**25%**

Table 18: ZINB regressions with pre-sample observations and robust standard errors (Opportunity Inflation Model).

Model 1	Variable	Estimates 1	Estimates 2
Patent $\#_t$	Pre-observation Patents	0.0765**	0.0779**
		(0.0301)	(0.0311)
	Patent Stock_{t-1}	0.597***	0.568***
		(0.0821)	(0.0802)
	Public funding_{t-1}	0.266	0.283*
		(0.174)	(0.172)
	ln(share of funding from $\text{industry})_{t-1}$	0.791***	0.785***
		(0.281)	(0.283)
	ln(publications in last 3 $\text{years})_{t-1}$	0.176	0.0661
		(0.126)	(0.136)
	ln(avg JIF in last 3 $\text{years})_{t-1}$		0.507**
			(0.207)
	Promotion_{t-1}	0.214	0.201
		(0.165)	(0.168)
	Peer patents_{t-1}	0.181**	0.184**
		(0.0715)	(0.0715)
	Peer patents^2_{t-1}	-0.00668***	-0.00667***
		(0.00219)	(0.00218)
	Professor inventor_{t-1}	0.967***	0.942***
		(0.256)	(0.261)
	ln(department funding in 3 last $\text{years})_{t-1}$	-0.167	-0.186
		(0.201)	(0.203)
	Industry orientation of department_{t-1}	0.205	0.142
		(0.760)	(0.737)
	Research orientation of department_{t-1}	0.0267***	0.0264***
		(0.00990)	(0.0100)
	Department staff_t	-0.0129	-0.0128
		(0.0132)	(0.0130)
	RAE_t	-0.375	-0.432*
		(0.249)	(0.252)
	TTO staff_t	-0.00182	0.000229
		(0.0145)	(0.0140)
	Year Dummies	YES	YES
	University Dummies	YES	YES
	Constant	-3.369	-3.421
		(2.576)	(2.582)
Inflation (logit)			
	Low Publication Activity_{t-1}	30.79***	30.36***
		(4.002)	(3.927)
	Low Funding Activity_{t-1}	28.98***	28.57***
		(6.302)	(6.316)
	Chemical Engineering_t	ommitted	ommitted
	General Engineering_t	-16.17***	-16.28***
		(0.822)	(0.894)
	Mechanical Engineering_t	13.16**	12.67**
		(5.643)	(5.549)
	Electrical and Electronic Engineering_t	-32.68***	-45.42***
		(2.509)	(2.285)
	Civil Engineering_t	9.358	8.645
		(30.68)	(33.73)
	Promotion_{t-1}	1.262	1.366
		(1.784)	(1.774)
	Constant	-44.12***	-43.33***
		(10.14)	(10.10)
	Log-Likelihood	-1034.192	-1031.272
	Ln-alpha	0.579***	0.557***
	Zero Observations	3837	3837
	Observations	4121	4121

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: ZINB regressions with pre-sample observations and robust standard errors (Support Inflation Model).

Model 2	Variable	Estimates 1	Estimates 2
Patent #$_t$	Pre-observation Patents	0.0727**	0.0748**
		(0.0309)	(0.0322)
	Patent Stock$_{t-1}$	0.589***	0.564***
		(0.0821)	(0.0811)
	Public funding$_{t-1}$	0.290	0.296
		(0.191)	(0.190)
	ln(share of funding from industry)$_{t-1}$	0.827***	0.816***
		(0.287)	(0.288)
	ln(publications in last 3 years)$_{t-1}$	0.232**	0.138
		(0.114)	(0.124)
	ln(avg JIF in last 3 years)$_{t-1}$		0.448**
			(0.195)
	Promotion$_{t-1}$	0.194	0.181
		(0.151)	(0.152)
	Peer patents$_{t-1}$	0.174**	0.177**
		(0.0798)	(0.0811)
	Peer patents$^2_{t-1}$	-0.00595**	-0.00602**
		(0.00239)	(0.00241)
	Professor inventor$_{t-1}$	0.684**	0.689**
		(0.287)	(0.290)
	ln(department funding in 3 last years)$_{t-1}$	-0.248	-0.291
		(0.301)	(0.299)
	Industry orientation of department$_{t-1}$	-0.611	-0.536
		(1.009)	(1.007)
	Research orientation of department$_{t-1}$	0.0313***	0.0311***
		(0.00960)	(0.00971)
	Department staff$_t$	-0.0114	-0.0119
		(0.0169)	(0.0169)
	RAE$_t$	-0.546*	-0.563*
		(0.320)	(0.318)
	TTO staff$_t$	-0.00158	-0.000648
		(0.0169)	(0.0164)
	Chemical Engineering$_t$	ommitted	ommitted
	General Engineering$_t$	-0.672	-0.576
		(0.518)	(0.524)
	Mechanical Engineering$_t$	-0.613	-0.491
		(0.451)	(0.453)
	Electrical and Electronic Engineering$_t$	0.0847	0.140
		(0.318)	(0.318)
	Civil Engineering$_t$	-0.867*	-0.775*
		(0.445)	(0.435)
	Year Dummies	YES	YES
	Constant	-2.080	-1.853
		(3.837)	(3.783)
Inflation (logit)			
	ln(funding in 3 last years)$_{t-1}$	-0.387**	-0.382**
		(0.156)	(0.153)
	ln(department funding in 3 last years)$_{t-1}$	-0.963	-1.041
		(1.029)	(1.030)
	Department staff$_t$	0.00766	0.0105
		(0.0432)	(0.0456)
	TTO staff$_t$	-0.283***	-0.285**
		(0.104)	(0.113)
	Constant	17.44	18.26
		(12.57)	(12.70)
	Log-Likelihood	-1037.094	-1034.792
	Ln-alpha	0.516***	0.497***
	Zero Observations	3837	3837
	Observations	4121	4121

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 20: Characteristics of the certain zero group (Opportunity Inflation Model).

Certain Zero Observations (472)				
Mechanical Engineering	249	25%		
Chemical Engineering	5	1%		
Civil Engineering	218	36%		
	Mean	SD	Min	Max
Publications in last 3 years	0.255	0.271	0	0.667
Yearly funding in 3 last years	£59	£263	0	£1,928

APPENDIX A

DEVELOPMENTS IN THE UK

The UK provides a good background for analysis of university-industry collaboration and its effect on the individual researcher due to its unique characteristics. It is a clear example of a market oriented university system which developed via two different approaches to government funding. Initially funding was reduced to promote research activities that attract funding from non-governmental sources, and later was increasingly allocated through mission oriented grants to indirectly control universities' research agendas (Geuna, 1999). The selective funding policies introduced in the UK represent a model by which the changes in other European countries may be emulated. An understanding of the UK system may therefore provide insight to better direct the evolution of other systems in Europe (Geuna, 1997).

UK government policies aimed at directing academic research developed in the mid 1970s when the Science Research Council (SRC; a predecessor to the Engineering and Physical Science Research Council (EPSRC)) decided to support research of economic or industrial relevance (Senker, 1998)[1]. During the 1980s, policies to promote the societal impact of university research became more widely spread. The government reduced block funding to universities and replaced it with selective grants, hoping that restrictions in public funding would encourage links with industry (Geuna, 1997). At the same time, several government programmes were set up to support collaborative research[2], however, with little success (Senker, 1998).

Since the 1990's a series of policy papers and advisory reports urged the government to reform the public research system and encourage industry collaboration (Dearing, 1997; Lambert, 2003; Sainsbury, 2007). These reports raised awareness of the importance of knowledge exchange initiatives amongst university managers and established them as a

[1] It was also responsible for the Teaching Company Scheme, set up to connect businesses with the science base.

[2] E.g. the LINK Programme launched to "bridge the gap between the research base and industry" (Senker, 1998: 29)

third goal of universities. In addition, government backed its campaigns with financial resources, providing incentives to universities to move in its policy direction (Tapper, 2007). For instance, the Funding Council introduced several programmes to enhance the contribution of science to the economy[3]. These programmes encouraged universities to set-up technology transfer offices to connect to businesses and to exploit their research, partly because of the way these funds are allocated (a formula that is partly driven by income from contract research and commercial activity). It became apparent that a "link between government funding and the pursuit of its desired policy goals has developed" (Tapper, 2007: 157).

Since the 1980s the share of government funding distributed on a competitive basis has increased from 19% to 43% in 2003 (Geuna, 2009). However, the allocation of these funds is highly skewed. The majority of Research and Funding Council grants are concentrated in just a few institutions. In 2006/07 the upper decile received £51,660K, with £2,467K for median universities and nothing for the lower decile. The distribution of income from commercial contracts is equally skewed. The majority of industry funding goes to high prestige institutions, with most of the grants concentrating in specific science and engineering departments (HEFCE, 2009; Senker, 1998). A median universities receives £3100K, universities in the upper decile receive £15219K and those in the lower decile again nothing (UUK 2008). Universities in the UK are by now faced with fierce competition for funding from government and industry, with a large number facing severe financial problems.

[3]E.g. Higher Education Reach Out to Business and Community in 1999 and replaced by the Higher Education Innovation Fund in 2001, allocating funds of around £20 million per year on a competitive basis.

APPENDIX B

DESCRIPTION OF THE DATABASE

The basis for this thesis is a longitudinal dataset containing detailed information on engineering academics that were employed at the Engineering departments of 40 major UK universities between 1985 and 2007. The data was collected at City University, London as part of the ESRC project "Benefits and cost of knowledge and technology transfer: A panel data analysis" in 2008/09 and is partly available to other researchers through the Economic and Social Data Service (ESDS). The dataset is the first comprehensive longitudinal data available on academic researches that includes the whole population of academics employed at the studied engineering departments over the observation period, not only successful academic inventors. The dataset comprises information on academics' publication, patents and external funding sourcing activity.

The project concentrates on the engineering sector, as it has traditionally been associated with applied research and operates between the two spheres of fundamental science and application of technology, "transforming knowledge from ideas to operational concepts" (Foray and Lissoni, 2010). Further, engineering is the discipline most relevant to industry that contributes substantially to industrial R&D (Cohen et al. 2002). Indeed, US universities first established engineering as a discipline, to serve the needs of the local community and local industries (Rosenberg and Nelson, 1994).

Also, industry collaboration amongst academics in engineering departments in the UK is better recorded than in other disciplines. It has to be noted, however, that engineering differs substantially from other fields within the sciences, especially in its highly fragmented and applied character. Any interpretation of results in this thesis has to consider this before appropriating them to other fields of science.

B.1 Construction of the database

University List As a first step in the data gathering process we collected the names of universities with engineering departments from the 2001 Research Assessment Exercise

(RAE). The RAE is a survey of research excellence conducted by the UK Funding Councils every 5 to 7 years to rank university departments and form a basis for funding allocation. This first search revealed 80 universities with active engineering departments in the UK. As a second step we tried to locate university calendars and prospectuses that display faculty staff information for each of the 80 universities for the period 1985 to 2007[1]. Calendars containing staff information were available for 40 universities. These include all 19 universities with engineering departments that are part of the prestigious Russell Group, a coalition of large, research intensive UK universities and an additional 21 universities including both, comprehensive universities and technological universities. 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.

Academics' names and rank The calendars provided complete lists of the universities' academic staff with names and academic ranks of university researchers. Data collection focussed solely 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. Through careful cross-analysis we identified those researchers that held positions in more than one of the engineering departments in our dataset during their career. This information was matched and we were able to trace researcher careers across universities. In total information on 7707 individuals was collected. It should be noted, that academics leave (and join) our dataset at different stages in their career, when they move to (or from) abroad, industry, departments other than engineering (e.g. chemistry, physics, computer science), or universities not part of our dataset. A small number of researchers also re-enters the dataset after some years of absence.

Publication data Data on publications was derived from the ISI Science Citation Index (SCI). Using surnames, first initial and university affiliation we collected all the articles published by the researchers in our database while they were employed at one of the 40

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

institutions. Most entries in the SCI include detailed address data that allow us to identify institutional affiliations and unequivocally assign articles to individual researchers[2]. We moreover carefully checked article titles and research topics to avoid mismatches for popular names. The resulting publication database contains information on the number of co-authors and journal ISSNs for each of the publications. Journal ISSN information was matched with the ISI Journal Citation Reports to assign the Journal Impact Factor (JIF) to each publication. The JIF is a measure of importance attributed to a journal based on the number of citations the journals received in the three years following its publication and is an indicator for the quality of a journal in which an article appears[3]. We further obtained the Patent board (formerly CHI) classification (version 2005) of the basicness of journals, developed by Narin et al. (1976) and updated by Kimberley Hamilton for the National Science Foundation (NSF). The measure is based on cross-citation 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. The classification only contained SCI journals published in 2005; hence not all journals in our database could be assigned a value of appliedness.

Collaborative research grants The majority of 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, and its predecessor the Science and Engineering Research Council (SERC). Data on these grants is available from 1986 onwards. Driven by recent policy developments the EPSRC encourages commercial and collaborative research and as a result since 1995 around 40% of grants have involved partners from the industry. The EPSRC provided us with a database containing information on the start year and duration of grants, total amount of funding, names of principle and co-investigators, institution of the principle investigators (grant receiving institution) and names of partner organisations. The names of both principal and co-investigators were matched with names

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

[3]Reports for all the years starting from 1985 were available from the British Library. We were hence able to consider all SCI journals and to allow for variation in JIF

in our database. The partner organisations were coded according to their characteristics in terms of partners from industry and partners from public bodies or government. All the partner names were searched on the internet and their websites screened to identify them as businesses. Research grants that involved at least one partner from industry were then identified as collaborative research projects.

Additionally to the EPSRC data we approached the 40 universities in our dataset to provide us with external grant information. 22 universities responded to our call. Seven submissions were incomplete, either missing researchers' names, year information or excluded funds from industry. Of the remaining 15 universities only 10 submitted grant information for more than 10 years. Further, the majority of submissions only included information on principal investigators. We therefore were only able to match external grants at 10 out of 40 universities for a 12 year period (1996-2007) for principal investigators. The data provided by the universities was already coded according to nature of the funding body and allowed us to identify grants from an industry sponsor.

Patent data Patent data was obtained from the European Patent Office (EPO) database. The matching process was very lengthy and required intensive manual cleaning of the data. This was necessary to collect all a researcher's patents including those filed with universities or filed with misspelled names. As a first step, researcher surnames and first initials were used to extract patents from the EPO database. A broad matching exercise based on surnames, first names and initials (2nd and 3rd initials) eliminated researchers with very different names. A filtering exercise then excluded patents based on age, address information, and subject area. The age-filter excluded patents filed before the researcher started university education. This filter could not be used for all academics in the sample but only those for who age information was available from personal websites. The address-filter eliminated patents by inventors living "too far" from the academic's work place. This filter was used with great caution as academics are often affiliated with several institutions and may live far from their university. Instead, the address-filter mainly served to link patents identified based on other criteria with others of the same address. The subject filter represented the most important filter in our analysis. Based on discipline matching and manual matching of patent descriptions with publication titles, patents truly by one of the researchers in the dataset could be identified.

The EPO database is problematic as many inventions have multiple entries. It was therefore necessary to compare priority numbers to ensure that each invention is only included once in our data. We additionally employed the Derwent World Patent Index (DWPI) that contains information grouped around a base patent (the original invention). The DWPI further allowed us to acquire cleaned and formatted data on patent assignees and family size[4]. For each patent we collected the year of filing [5], the names of patent assignee and the number of associated patents (family size).

The EPO does not cover patents that are only filed with national patent offices, e.g. the UK Intellectual Property Office (UKIPO). For a subsample of 479 researchers at the 10 universities that provided sufficient external grant information and that remained in the sample for the full period 1996 to 2005, we also collected information for patents filed with patent offices other than EPO and those filed before the observation period to build an inventor's profile. The patents were collected from the online search engine of the EPO and matched according to the criteria described above. As a result of this additional data collection in 2010, patents filed up to 2007 could be included for this subsample.

Demographic Information For the same subsample of 479 researchers, we tried to identify year and topic of their PhD. This information was collected from theses.com which lists theses submitted at universities in the UK and Ireland and gives the date of the PhD and the name of the degree awarding institution. Theses.com only contains surname and initials and we carefully matched the names in our database with those on the website. Again, we considered age and subject-filters to identify our researchers. The age-filter excluded PhD theses submitted before 1950 or before the researchers turned 24. The subject-filter compared names of dissertations with those of articles she published during early stages of her career to identify the correct entries. In total we were only able to identify theses for 407 researchers.

[4]While the EPO database is freely accessible and basic information on CD was provided to us free of charge from EPO, access to the DWPI is very costly and could therefore only be used at the British Library at a second stage of our data collection process.

[5]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

B.2 Problems of the Data

While the data collected for this thesis is the most comprehensive data on academics' collaboration and research activity available, comprising information on publications, patents, industry grants and collaborative research council grants, it is important to point out some of its main problems:

1. The unbalanced nature of the dataset with unknown entry and exit motivation.
2. The different sources for external funding information with little evidence for comprehensiveness and comparability.
3. A limited time-period with no pre-sample or initial period information.
4. Type II errors (false negatives) in data matching.

As mentioned above, researchers enter, exit and re-enter the dataset at several occasions. However, we have no information on their motivation, and no full record of their academic activity to infer these motivations. This has to be seen as the greatest limitation of our data. Future analysis should attempt to understand the reasons for entry and exit by identifying new entries to the profession and retiring academics based on PhD year or age information and to infer motives for other researchers from the analysis of academics moving between the departments contained in our dataset.

The second problem refers to the fact that our external funding information relies on data provided by the research offices of the universities. We believe that the data was submitted to the best knowledge of local research offices; however, we cannot be certain about its comprehensiveness. More importantly, grant information may be collected differently at the different institutions. However, it can be reasonably assumed that the data provided to us is similar in nature to data provided by universities to the RAE, following standardised patterns of collection and compilation.

The third concern regards the limited time-scale of the data. The science production process is a dynamic process where current performance is strongly influenced by past performance and the researcher's knowledge stock. We have, however, little information on the researcher's stock of knowledge which limits our ability to separate learning effects from ability. For a subsample of scientists we added pre-sample period information on patenting to our data. Similarly it might be desirable to collect similar data on publications in the pre-sample period and for a larger number of academics. Grant information, unfortunately, is not available beyond what we were able to collect. We hope that the size of our panel is sufficient to infer learning effects in academia.

The last limitation of our data refers to the problem of name matching in data collection. Misspellings and missing information is apparent in all databases used to build the dataset. We have mitigated this problem to a large extent by performing extensive manual checks. There is, of course, the possibility that we were not able to identify all the research outcomes associated with a researcher. Especially in cases of uncertainty we opted for excluding data rather than falsely including it in our dataset. With these caveats, the data, as presented here, is comprehensive to the best of our knowledge.

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