Research Policy 40 (2011) 55–68

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

The impact of academic patenting on university research and its transfer

Gustavo Crespi[a], Pablo D'Este[b], Roberto Fontana[c], Aldo Geuna[d,e,f,*]

[a] Science and Technology Division, Inter-American Development Bank (IADB), USA
[b] INGENIO (CSIC-UPV), Institute of Knowledge and Innovation Management, Spanish Council for Scientific Research (CSIC) – Polytechnic University of Valencia (UPV), Spain
[c] Department of Economics, University of Pavia, & KITeS – Bocconi University, Italy
[d] Department of Economics S. Cognetti de Martiis University of Torino, Via Po 53, 10124 Torino, Italy
[e] Collegio Carlo Alberto, Italy
[f] Grenoble Ecole de Management, France

ARTICLE INFO

Article history:
Available online 9 November 2010

Keywords:
Crowding-out/in effect
Academic patenting
Complementarities among knowledge transfer activities

ABSTRACT

This paper contributes to the ongoing debate on the impact of academic patenting on publishing and knowledge transfer. Drawing upon two separate surveys of academics, and their CV information, we provide empirical evidence for UK academics in engineering and physical sciences. The contribution of this paper is two-fold. First, our findings show that (the intensity of) academic patenting complements publishing up to a certain level of patenting output, after which we find evidence of a substitution effect. We also find weak evidence of important differences across scientific fields with the more basic-oriented fields showing indications of a crowding-out effect. Second, our analysis of the potential impact of patenting on knowledge transfer shows a positive correlation between the stock of patents and engagement in knowledge transfer channels. However, we find that a substitution effect sets in, indicating an inverted U-shaped relationship between patenting and several knowledge transfer channels.

1. Introduction

A large body of literature has developed in the last few years on the evaluation of the relationship between increased patenting by university researchers and their publication output. The evidence so far is contradictory. Some studies highlight the negative effect of patenting on the research output of scientists; others provide evidence of complementarity effects between the two activities. Statistical evidence, based mostly on the US (Agrawal and Henderson, 2002; Thursby et al., 2001), but also the EU (Breschi et al., 2007; Geuna and Nesta, 2006), indicates that, at least for top academics, there is no evidence of a substitution effect between these activities.[1] Top researchers both publish and patent, and a high patent output does not seem to negatively affect their publication output.

Starting from this evidence, we attempt to address two gaps in the literature. One is the lack of systematic evidence for the UK with respect to the relationship between publishing and patenting. On the basis of a sample of researchers from two major London universities, Banal-Estanol et al. (2010) present evidence of a positive relationship between publishing and industry contracts (although very high levels of interaction negatively affect research productivity), but find only weak evidence of a correlation between patenting and publishing. The second gap is the lack of analysis on the effect of increased patenting activity on the other channels of knowledge transfer between university and industry. The main issues addressed in this paper are the effect of past patenting on: (a) the publication outputs of academic researchers and (b) on academics' activities associated with knowledge transfer to industry and commercialization of research.

We gathered primary data from a large sample of UK academic researchers and built a longitudinal database for a sub-sample of researchers on the basis of their CVs. Given the major importance in Europe of university-invented patents[2] (Crespi et al., 2006), we paid particular attention to their identification and inclusion in the total patenting count for our sample of academic researchers.[3] We find that about 20% of researchers have some form of patenting experience.

Although we know a fair amount about the complementary relationship between patenting and publishing for the group of top scientists, we know much less about the rest of the population: those researchers who are research active, but are not among the

* Corresponding author. Tel.: +39 0116703891; fax: +39 0116703895.
E-mail address: aldo.geuna@unito.it (A. Geuna).

[1] See the *EINT* Special Issue edited by Geuna and Mowery (2007) for an assessment of the situation in Europe and the US.

[2] These are patents with at least one academic inventor (some research was conducted at the university), but whose assignees are not the university (usually a company).

[3] In other words, our sample includes academic inventors whose patents are owned by a university, and academic inventors whose patents are owned by a third party, and also non-patenting researchers.

0048-7333/$ – see front matter
doi:10.1016/j.respol.2010.09.010

top percentile in terms of productivity. The results of the present study show that academic patenting complements publishing at least up to a certain level of patenting output, after which there is some evidence of a substitution effect. We also find weak evidence of a scientific field effect, with the most basic sciences (Physics and Chemistry) showing evidence of a crowding-out effect (i.e. higher levels of patenting associated with lower levels of publishing), and Computer Science and Engineering showing evidence of a crowding-in effect (the higher the number of patents, the higher the number of publications). We know that academic output is strongly affected by the current and historical availability of funding: scientific (and technological) performance depends upon cumulative and self-reinforcing phenomena, described in the literature as the Matthew effect (Merton, 1968; Dasgupta and David, 1987, 1994). Though our models try to estimate the direction of causality, we are not able properly to evaluate the impact of funding on publishing and patenting. Thus it would be more accurate to refer to co-occurrence rather than complementarity between publications and patents. Also, our analysis of the impact of patenting on knowledge exchange channels with industry indicates that the impact of patenting takes a positive but inverted U-shape. In other words, the correlation between stock of academic patents and knowledge-transfer channels is positive up to a maximum number of patents, after which a substitution effect sets in.

The paper is organized as follows: Section 2 reviews the literature and sets out the main topics addressed in this study; Section 3 describes the data; Sections 4 and 5 present the results; and Section 6 concludes.

2. Emerging evidence on academic patenting and knowledge diffusion

In response to technological opportunities, policy initiatives and organizational changes, researchers (and universities) have become much more proactive in their efforts to commercialize scientific discoveries. In both the US and Europe, there has been a major increase in academic patenting since the 1980s, and UK universities have increased their technology transfer activity, reflected by the increased number of university Technology Transfer Offices (TTOs) set up during the 1990s: from 23 TTOs before 1990 to 116 in 2002 (NUBS, 2003). This institutional development has been accompanied by a significant increase in patenting activity: for example, in the period 2000–2004 invention disclosure increased from 2159 to 3029 (HEFCE, 2006). Alongside the well-documented increase in university-owned patents, there is robust evidence of a major increase (especially in Europe) in the number of individual academic scientists listed as inventors in the patents owned by third parties (Geuna and Nesta, 2006; Lissoni et al., 2008). It is debateable, however, whether the increase in academic patenting in the last quarter of the 20th century, has been beneficial for or detrimental to academic scientific performance, and to the alternative mechanisms for knowledge transfer and commercialization of the results of academic research.

2.1. Relationship between academic patenting and publishing

The increased involvement of academic researchers in patenting activity is raising concerns among scholars and policymakers about how this activity will impinge on the development of future scientific knowledge. The impact and reward systems for research in the academic and private sectors are fundamentally different in terms of: (1) the relationship between disclosure vs secrecy; and (2) the complementarities or substitution effects between public and private research expenditure (Dasgupta and David, 1987, 1994). Practices and norms in the private and public realms are different and can result in conflicts (Dasgupta and David, 1994; Stern, 1995; Nelson, 2004). These concerns echo earlier unease among scholars about the implication of academics' commercial involvement on the Mertonian norms and values guiding academic science (Merton, 1968; Mitroff, 1974; Mulkay, 1976).

The intention here is not to review this debate. Rather we want to highlight how a substitution effect can emerge, by discussing briefly two main concerns in the literature. First, critics of increased patenting fear that the involvement of academic researchers in this activity might lead to systematic changes in their research agendas, and a re-orientation towards research that is more likely to generate patentable results and more relevant to industry funders. Changes in research agendas are often related to a shift towards more applied research, referred to as the 'skewing' problem (Florida and Cohen, 1999). Second, concerns have been raised about the negative impact of academic patenting on the norm of swift publication of research results (to obtain priority) and the opportunity for open discussion among colleagues. Within the academic community, researchers disseminate information freely via publications in order to gain priority and promote continuous investigation to stimulate further advances. Patenting, however, requires novelty and thus secrecy prior to patent filing dates. These different incentives create challenges with regard to both the dissemination of information and access to research results (Hane, 1999). For example, some publications may be delayed or suppressed because of requests from firms to keep information (temporarily) confidential, at least until a patent is granted.

Finally, the sociology literature highlights that scientific fields are characterized by differences in the ease of the university–industry interactions. In particular, it has been argued that in the Transfer (Blume, 1990) or Pasteur's Quadrant Sciences (Stokes, 1997), such as biotechnology or informatics, codification of new knowledge can be achieved through publications or patents, at relatively lower costs for translation from one to the other, compared to other scientific fields, and that both types of outputs are accepted by the two epistemic communities. Following this argument, we would expect complementarity between patenting and publishing, to be more difficult in the more basic oriented scientific fields, than in the Transfer Sciences.

A large number of studies has focused on analysing the relationships between academic patenting and publishing. The empirical evidence is mixed. Assessments of academic scientists find that patenting skews research agendas toward commercial priorities, causes delays in the publication of research findings, and crowds out efforts dedicated to the production of public research (see, among others, Blumenthal et al., 1996; Campbell et al., 2002; Krimsky, 2003). Murray and Stern (2007) provide some evidence of a small 'anti-commons' effect of publication–patent pairs. Evidence against the linear complementarity between patenting and publishing is provided in Fabrizio and Di Minin (2008), where the findings indicate that for very high levels of patenting activity a crowding-out effect sets in. Also, Breschi et al. (2008) find a weak negative effect at very high levels of patenting among Italian scientists. Finally, Calderini et al. (2009), find evidence of a complementary effect among scientists in Material Engineering, but a strongly negative (substitution effect) for Material Chemistry when only publications in basic science are considered. All these studies suggest the presence of tradeoffs between patenting and research publication.

However, there is another group of empirical studies that provides strong evidence that star scientists also actively engage in patenting. Agrawal and Henderson (2002) study patenting activity for a 15-year panel of 236 scientists in two departments in the Massachusetts Institute of Technology (MIT). They find that increased patenting activity is correlated with increased citations to faculty members. Azoulay et al. (2007) show that patenting has a positive effect on publication rates for a sample of university researchers working in areas related to biotechnology. Markiewicz and Di Minin (2004) report a statistically significant positive effect of researchers' patent stocks on their publication counts, based on a sample of 166 academic inventors matched to an equal number of non-patenting scientists. Similarly, Thursby and Thursby (2004) provide information on the invention disclosure behaviour among faculty members from six research universities, between 1983 and 1999. They find disclosure to be positively related to publication, and a measure of department quality. Finally, the empirical work of Stephan et al. (2007), examining the relationship between patenting and publishing for a sample of doctoral graduates, finds patenting and publishing to be complementary. Breschi et al. (2007), Carayol (2007) and Gulbrandsen and Smeby (2005) obtain similar results for European academic patenting. Overall, these studies show that academic researchers that are involved in patenting are also very active in publishing. Some papers present strong evidence of co-occurrence (complementarity) between these research outputs; others find no evidence of a substitution effect. Evidence for both the US and Europe indicates that high quality university scientists are also active in patenting; patenting can be preceded by higher than normal scientific productivity or followed by a flurry of publications (such as in the Italian case). These studies also show evidence of life-cycle effects.

This brief literature review indicates that findings are mixed with regards to the relationship between patenting and publishing among academics. While there is some statistical evidence of a complementarity effect (co-occurrence) between publishing and patenting, there is also qualitative and quantitative evidence of crowding out, highlighting the presence of non-linear relationships between patenting and publishing.

2.2. Relationship between academic patenting and knowledge transfer

Channels for university knowledge transfer include: attendance at meetings and conferences, student placements, research collaborations, contract research, consultancy work, spin offs and/or joint university–industry supervision of PhDs (Cohen et al., 2002; D'Este and Patel, 2007; Bekkers and Bodas Freitas, 2008). Little is known about whether these channels are complementary to or in conflict with academic patenting. A better understanding of this issue is important because many policy initiatives that encourage patenting of publicly funded research (e.g. the Bayh–Dole Act) are based upon the rationale that these policies encourage knowledge exchange between universities and business (Kenney and Patton, 2009). However, if patenting is not positively associated with other interaction channels, then policies encouraging universities to patent and license might be misaligned with the diverse nature of the exchanges between universities and industry (Agrawal and Henderson, 2002).

Evidence of a complementary or a substitution effect between patenting and other channels of knowledge transfer with industry, as in the case of the patenting-publishing relationship, is mixed. On the one hand, there are some studies that suggest that most forms of university–business interaction involve elements of research collaboration (Perkmann and Walsh, 2008) and, in particular, that academic patenting is often associated with other channels of knowledge transfer. For instance, some studies show that the involvement of academic inventors is often required to bring a patented technology to market, given the embryonic nature of most patented inventions, thus inducing a tight coupling between patent agreements and collaborative partnerships (Jensen and Thursby, 2001; Agrawal, 2006). Also, several studies find that academics with long experience of collaboration with industry are more likely to exploit a broader range of knowledge-transfer channels (D'Este and Patel, 2007; Landry et al., 2007), and more likely to be involved in patent applications (Amara et al., 2009). This co-occurrence is likely to be a consequence of the fact that collaborative partnerships with businesses contribute to creating awareness about the commercial exploitation of academic research and promoting a better understanding of the marketplace, thereby increasing the chances of academics engaging in patenting and commercialization activities (Shane, 2000; Siegel et al., 2003).

On the other hand, evidence supporting the presence of complementarities has been challenged by anecdotal evidence – from both Europe and the US – of tensions between companies and managers of university technology transfer offices. Commenting on the decline in the US of industry funding for academic research between 2002 and 2004, Bhattacharjee (2006), on the basis of interview material, suggests that conflicts may be related to academic institutions becoming increasingly aggressive in claiming and protecting intellectual property rights (IPR) on inventions arising out of industry-funded projects with the consequence that negotiations are more difficult and time consuming. Destler (2008) argues that the so called 'Gatorade factor' may induce universities to demand such high IPR and royalty payments from corporations that negotiations over potential collaborations break down before any cooperative activity is undertaken.[4] Even in those cases where projects do get off the ground, excessive levels of bargaining may become an obstacle to their completion. Gewin (2005) argues that disputes can lead industry to withdraw from collaborating with university, especially if a project is likely to result in several patents and the university overvalues its IPR. Alongside these anecdotal accounts, there is some statistical evidence of possible consequences from ongoing tensions. Valentin and Jensen (2007) provide evidence that since a new Bayh–Dole-inspired reform of university patent rights was introduced in Denmark, biotech firms have largely withdrawn from collaborations with university scientists. They suggest that the main reason for this is that ex-ante negotiation over IPR imposed by the new regulation is not commensurate with the conditions of exploratory, early-stage research characteristic of much biotechnology work involving universities and business, which supports the view that changes in university patenting regulations may have had a detrimental impact on exploratory research collaborations.

The studies referred to above show that while the phenomenon of academic patenting is well documented, its implications for both academic performance and the alternative mechanisms of knowledge transfer are uncertain. Our empirical study attempts to shed light on the UK case, where evidence is scarce.

3. Data sources and descriptive statistics

To investigate the issues discussed above, we collected information on the patenting activity of a sample of UK academic researchers in order to build a comprehensive dataset. We drew on a 2004 survey of academic researchers who had received grants from the UK Engineering and Physical Sciences Research Council (EPSRC)[5] in the period 1999–2003. The survey[6] was sent to 4337

[4] The 'Gatorade factor' refers to the high royalties received by the University of Florida for licensing its Gatorade drink formula which supposedly led other colleges and universities to increase their royalties on IPR developed by faculty members.

[5] The EPSRC is the UK's largest research council and its funding is focused on the Engineering and Physical Sciences. Research proposals submitted to the EPSRC are peer reviewed for scientific merit. While the EPSRC encourages partnerships between researchers and the potential users and beneficiaries of research (including firms), collaboration with third parties is not an eligibility requirement.

[6] The main objective of the survey was to collect information from academic researchers on patterns of knowledge-transfer activities, including information on involvement of academics on a range of possible interactions with businesses

Table 1
Total response rate.

Discipline	Population mailed	Positive reply	Response rate
Chemistry	212	61	28.77%
Computer Science	133	25	18.80%
Mechanical, Aero & Manufacturing Engineering	145	16	11.03%
Physics	176	69	39.20%
Total sample	666	171	25.68%

UK academic researchers in 10 scientific disciplines corresponding to the Physical Sciences and Engineering, and obtained 1528 responses.

We supplemented these data first, by collecting information from the CVs of a sub-sample of the survey respondents in order to construct a longitudinal PATPUB dataset covering the entire academic lives of these researchers. We used the PATPUB longitudinal database to study the relationships between patenting and publishing (see Section 4). Second, we collected information on patenting involvement for the full set of respondents to the original survey, to study co-occurrence between patenting and other channels of knowledge transfer (see Section 5). The data gathering process is described below.

3.1. The PATPUB longitudinal dataset on academic publishing and patenting

The data gathering process involved several steps. We started by collecting researchers' CVs and verifying and complementing the information with online sources. We selected all those survey respondents in the four disciplinary fields of Chemistry, Physics, Computer Science, and Mechanical, Aeronautical and Manufacturing Engineering for whom we had valid e-mail addresses; we contacted them via e-mail to ask for their cooperation in our study.[7] Of the 666 researchers contacted, we obtained 171 positive responses, a response rate of around 26%.[8] The nature of their responses varied from sending a web address (where information could be extracted), to attaching a CV, to providing a written outline of patenting and publication activity. The distribution of response rates across the four disciplines is presented in Table 1.

The second step was to create reliable information on the publication and patenting records of the academic researchers. While, in principle, CVs contain information on publications, they are often not up to date and not all references include information about the type of publication or journal in which work was published. To cross check publications in refereed journals, we used data from the ISI Web of Knowledge as a comparison.[9] Information in CVs on patenting was in the form of patent application numbers. Additional information such as year of filing, type of patent (i.e. whether the researcher is listed as an inventor on an industry owned patent, or whether the patent is university owned), and status (applied, granted, withdrawn, rejected) was extracted from the UK Intellectual Property Office, the European Patent Office (EPO) and the US Patent and Trademark Office (USPTO) databases. We found that 38% of academic inventors are associated only to university-invented patents, while 31% only to university-owned patents, the remaining 31% were associated with both university-invented and university-owned patents. Consistent with previous data on European university patents (Geuna and Nesta, 2006; Lissoni et al., 2008) only 25% of the patents are owned by a university because prolific inventors tend to be associated with many more university-invented than university-owned patents.

The final dataset is a panel that follows all academic researchers (inventors or not) from 1975 to 2005. The start date for the inclusion of an academic researcher in the panel is the year of PhD award: 1956 is the earliest year among our sample of researchers. For the 29 researchers who received their PhDs before 1975 we collected publication and citation data only from 1975 for reasons of data robustness related to the characteristics of the ISI data. After cleaning the data to control for incomplete and/or inconsistent observations, our dataset contained 3649 inventor-year observations. This corresponds to a total sample of 157 academic researchers, 36 inventors (they filed at least one patent between 1975 and 2004) and 121 academic researchers with no patenting activity in that period. The basic descriptive statistics are presented in Table 2.

The average number of publications per year is 2.9. While in the early 1980s less than 0.5% of researchers in our sample were named as inventors on a patent, in the early 2000s, 2% of researchers were listed as inventors on at least one patent.[10] Across the whole period considered, 23% of active academics had applied for patents one or more times.[11] Our average researcher is 46 years old and was awarded a PhD degree in the mid 1980s; 4% of the researchers in the sample are Members of the Royal Society; 38% have university chairs and the remaining 62% are research fellows/lecturers, or senior research fellows/senior lecturers/readers. Finally, 75% of the researchers in our sample are active in the field of Chemistry or Physics.

3.2. The cross sectional dataset on academic patenting and other channels of knowledge transfer

To construct a cross-sectional dataset on channels of knowledge transfer, we matched the names of survey respondents (i.e. 1528 individuals) to the information on inventors contained in patents granted by the EPO. Information on patents was collected from the CESPRI-EPO patent database, which contains information on all patents applied for and granted by the EPO since 1978. We were particularly interested in understanding whether the academics in our sample frame were inventors (i.e. inventors named on at least 1 EPO patent granted since 1978) and, if so, how many patents they had been involved in between 1978 and 2001. Matching of EPSRC grant recipients and the CESPRI–EPO database was on the basis of surname and initial(s).

To avoid problems related to inventors with the same surnames and initials, we matched the first two digits of the post code of the academic affiliationed to the first two digits of the post code

(including joint research agreements, contract research, consultancy, joint PhD training) and commercialization activities (i.e. setting up equity interests in companies, including formation of spin-offs). Further details on the survey are available in D'Este et al. (2005) and D'Este and Patel (2007). For details on the sampling frame and the response rates across disciplines see Table A1 in the Appendix A.

[7] For some respondents to the original survey we did not have correct or updated e-mail addresses. For about 20% of the respondents in the four fields selected we had no e-mail address.

[8] To ensure that star scientists were included in our sample, we collected information on UK Fellows of the American Physical Society (APS). We found 19 UK physicist members, 4 of whom responded to our request by the deadline.

[9] In order to minimize the probability of including incorrect information when extracting records from the ISI Web of Knowledge database, we implemented a systematic cleaning up algorithm (see Methodology Appendix).

[10] This trend could be over-estimated because we are not capturing potential inventors, who might have been developing patents in the 1980s and have since retired, and so are not included in the final dataset of researchers active in 2001.

[11] There could be two reasons for this high value. First, we consider both national (UK) and international (EPO and US) patents while other studies focus on one or other patent office. Second our starting EPSRC sample includes successful fundraisers in fields of research where collaboration with companies is more likely (i.e. engineering and physical sciences), which will increase the probability of being involved in patenting compared to academics in other disciplines.

Table 2
Descriptive statistics. PATPUB dataset.

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Pub_{it}	Publications Counts (annual)	157	2.90	2.82	0.07	20.40
P_i	Patent dummy	157	0.23	0.42	0.00	1.00
Gender_i	Dummy if female	157	0.10	0.29	0.00	1.00
Age_i	Age	157	46	10.54	28.00	74.00
PhD_i	Year of PhD award	157	1987	11.00	1956	2003
Prof_i	If professor at time of survey	157	0.38	0.49	0.00	1.00
Star_i	Dummy if member of a Royal Society	157	0.04	0.21	0.00	1.00
Times Cited_{it}	Average citations/paper/year	157	2.49	0.84	0.00	4.45
RAE_i	Department RAE score (2001)	157	4.92	0.94	2.00	6.00
Dep Size_i	Department size at survey time (log)	157	3.58	0.66	2.30	5.01
Chemistry_i	Dummy variable	157	0.36	0.48	0.00	1.00
Physics_i	Dummy variable	157	0.39	0.49	0.00	1.00
$\text{Computer Science}_i$	Dummy variable	157	0.15	0.35	0.00	1.00
Engineering_i	Dummy variable	157	0.10	0.30	0.00	1.00

of the inventor's address as it appears in the CESPRI–EPO database. Note, however, that this way of removing duplicates is not perfect: academics may change jobs or may commute some distance to where they work (i.e. they may live and work in places with different post codes). The latter case is more likely where universities are located on the edges of towns or cities, or in large cities with several different post codes (e.g. London). Thus, cleaning based on this criterion could underestimate the number of inventors in our sample of EPSRC survey respondents. As a robustness check for the EPO database matching, we compared our results with information on patenting records provided by the sample of university scientist for whom we have CV information. The matching with EPO data correctly estimated 81% of the cases in the sample confirmed by CV data.[12]

The matching process identified 249 inventors from our initial list of 1528 EPSRC grant recipients who responded to our survey. That is, 16% of our survey respondents are researchers who have been listed at least once as an inventor on a EPO granted patent, in the period 1978–2001. The basic descriptive statistics for the sample of 1528 respondents are presented in Table 3.

4. Impact of academic patenting on publishing

To assess the impact of an increase in academic patenting on the publications output of UK scientists, we follow a similar methodology to the one developed by Breschi et al. (2008). Using our whole sample of academics we estimate the following model:

$$Y_{it} = X_{it}^{'}\beta + \tau P_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (i = 1, \ldots N \quad \text{and} \quad t = 1, \ldots T) \tag{1}$$

where Y_{it} is a measure of research output (i.e. publications count), X_{it} is a set of time varying explanatory variables, μ_i is an individual fixed effect and λ_t is a set of time effects. P_{it} is a dummy variable that takes the value 1 for the years after the first patent was filed (including the year of filing) and 0 otherwise. The inclusion of an individual fixed effect controls for unobserved researcher characteristics that are constant over time and that might be correlated to both patenting activity and research output (e.g. ability, research productivity, etc.). A particular concern is that some correlation between patenting activity and the error term might remain even after controlling for an individual fixed effect. This might occur if some shocks on publication activity (ε_{it}) induced researchers to patent. In order to purge for this additional source of correlation we estimated the model using instrumental variables.

4.1. Basic results

Table 4 summarizes the results for five different specifications of Model (1).

Columns (1)–(4) report the results for the model estimated using a negative binomial regression approach without controlling for unobserved heterogeneity. In column (1) we control only for academic's age (and its square), time and field dummies (not reported in the table). The results suggest that publications follow a non-linear inverted U-shaped relationship with age. Publishing peaks at age 42. We find also that although the coefficient for patenting is positive, it is not statistically significant. Column (2) shows the results when controlling for researcher's unobserved ability using three observed variables: being a professor, average citations, and Royal Society membership. These dummy variables are all positive, but only the first two are significant. We control also for gender, which is not significantly different from zero, and year of PhD award, which is significant and negative, suggesting that researchers from more recent cohorts publish less, perhaps due to their shorter academic experience. Finally, quality of the researcher's department is positive, indicating that being a member of a high quality research department increases the publications output of researchers.[13] Department size is negatively correlated with publications, indicating an absence of economies of scale in knowledge production. It is interesting that, after including the set of additional control variables, the coefficient of the patenting dummy drops dramatically, remaining positive, but not significant (compare columns (1) and (2) in Table 4).

Column (3) controls for remaining unobserved heterogeneity by estimating a random effects binomial model. The coefficient for patenting activity in this case is negative, but not significant. The results in column (4) control for individual unobserved heterogeneity using the Hausmann et al. (1984) standard conditional negative binomial. It has to be noted that this standard fixed effects estimator does not control fully for all stable unobserved covariates, the reason being that it is based on a regression decomposition of the *overdispersion* parameter rather than the usual regression decomposition of the mean. A consequence of this procedure is that the time constant variables are not all wiped out in this model. The estimates in column (4) show a further decline in the coefficient of the patenting dummy, suggesting lack of complementarity between publishing and patenting. However, the coefficient remains not significant. Column (5) controls for any potential endogeneity of the patenting dummy by estimating instrumental variables. In this

[12] See Appendix B for a discussion of the robustness of our matching procedure.

[13] Department research quality is measured by the department's score in the Research Assessment Exercise (RAE), the periodic assessment of research quality that used to be carried out by the Higher Education Funding Councils.

Table 3
Descriptive statistics. Cross-sectional dataset.

Variable	Definition	Mean	Std. Dev.	Min	Max	Obs.[a]
Joint research	Value 1 if frequency is ≥1	0.45	0.50	0	1	1519
Contract research	Value 1 if frequency is ≥1	0.47	0.50	0	1	1525
Consultancy	Value 1 if frequency is ≥1	0.38	0.49	0	1	1527
Joint PhD Training	Value 1 if frequency is ≥1	0.34	0.47	0	1	1527
Spin-offs	Value 1 if frequency is ≥1	0.12	0.33	0	1	1525
Patent stock	No. of patents between 1978 and 2001	0.41	1.48	0	17	1504
Age	Age at survey time	45	10	23	75	1488
Professorial status	Value 1 if Professor at survey time	0.47	0.50	0	1	1522
RAE 2001 Low	Value 1 if dept. score was 4 or below	0.28	0.45	0	1	1518
RAE 2001 High	Value 1 if dept. score was 5*	0.29	0.45	0	1	1518
Dept. Size (ln)	Academic staff (average 1998–2001)	4.20	0.68	2.07	5.60	1525

[a] While the number of observations equals 1528 (the number of survey respondents), the valid observations for each variable varies as a consequence of missing data from survey responses.

case, we instrument the patenting dummy using as an instrument the proportion of academic inventors in the same scientific field (Wooldridge, 2002). As explained in Breschi et al. (2008) the rationale for this is that researchers who work in an environment where many researchers are involved in patenting will benefit from this experience and find patenting activity easier. If this is a correct assumption, this variable should show correlation with patenting activity but not with publication output, making it a valid instrument. Indeed, first stage results suggest that the instrument is strongly correlated to the patenting dummy and the instrument is not significant when included in the main regression. The results indicate that the coefficient for the patenting dummy is negative, non-significant and not statistically different from the previous results, suggesting that endogeneity is not a problem in our data. Overall, the results in columns (1)–(5) (and the results of the robustness check presented in Appendix C) suggest that patenting activity is not correlated to publications. Academic patenting has neither a positive nor a negative impact on scientific publishing.

Finally, we want to verify whether the introduction of a lag between patenting and publishing would modify our basic results in order to determine whether the decision to patent affects the future productivity of a researcher. Previous empirical work finds evidence that researchers might refrain from publishing until the patent is secured, or that there may be a resource effect (patenting brings in additional funding) which enables higher productivity after patent approval (Breschi et al., 2008). Table 5 presents the results of this analysis; the pooled negative binomial regressions include a fixed effect controlling for unobserved heterogeneity affecting levels of publication. All the regressions include the same control variables as in Table 4, as well as time fixed effects.

Column (1) in Table 5 includes a dummy variable that takes the value 1 for the years when patenting activity is observed, and zero otherwise. In this way, we try to capture any special shock that might be contemporaneous with the filing of a new patent application, and also transitory ($Pyear_{it}$). The results suggest that neither the patenting regime nor year patenting dummies are significantly different from zero. We tried several specifications – that move $Pyear_{it}$ 1 and 2 years into the future or that lag it 1 or 2 years into the past. Columns (2) and (3) in Table 5 show the results for $Pyear_{it}$ moved forward 1 and 2 years respectively. Our

Table 4
Negative binomial regressions of publication counts.

Coefficient	(1)	(2)	(3)	(4)	(5)
P_{it}	0.239	0.112	−0.016	−0.042	−0.030
	[0.158]	[0.130]	[0.058]	[0.062]	[0.698]
Age_{it}	0.340***	0.256***	0.231***	0.215***	0.194***
	[0.027]	[0.025]	[0.016]	[0.023]	[0.025]
Age^2_{it}	−0.004***	−0.003***	−0.003***	−0.003***	−0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Gender_i		0.178	0.196	0.538	0.574
		[0.203]	[0.143]	[0.335]	[0.352]
PhD_i		−0.063***	−0.071***	−0.101***	−0.105***
		[0.012]	[0.012]	[0.020]	[0.021]
Prof_i		0.440***	0.281***	−0.041	−0.042
		[0.120]	[0.102]	[0.179]	[0.183]
Star_i		0.405*	0.418**	0.715**	0.705**
		[0.233]	[0.181]	[0.315]	[0.321]
Times Cited_i		0.140	0.193***	0.051	0.065
		[0.093]	[0.070]	[0.135]	[0.137]
RAE_i		0.130*	0.099**	0.181**	0.188**
		[0.067]	[0.047]	[0.083]	[0.084]
Dep Size_i		−0.161*	−0.105	−0.209*	−0.215*
		[0.088]	[0.064]	[0.119]	[0.121]
Constant	−6.224***	119.061***	135.621***	195.810***	204.482***
	[0.496]	[23.927]	[23.550]	[39.895]	[41.183]
Observations	3649	3649	3649	3649	3540
Number of idinv	157	157	157	157	157

Time dummies and field dummies included.
All pooled regressions include robust standard errors clustered on individuals to allow residuals to be correlated within each individual block. (1) Pooled regression, (2) Pooled regression, (3) Random Effects, (4) Fixed Effects, (5) Fixed Effects instrumental variables.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 5
Negative binomial regressions of publication counts (for different definitions of patenting activity).

Coefficient	(1)	(2)	(3)	(4)	(5)
P_{it}	−0.037	−0.057	−0.055	−0.049	−0.015
	[0.064]	[0.86]	[0.79]	[0.77]	[0.23]
$Pyear_{it}$	−0.037	−0.15	−0.233	0.129	−0.01
	[0.119]	[1.17]	[1.69]	[1.18]	[0.09]
Age_{it}	0.215	0.209	0.229	0.197	0.173
	[9.31]**	[8.41]**	[7.24]**	[8.45]**	[7.38]**
Age^2_{it}	−0.003	−0.003	−0.004	−0.003	−0.003
	[24.28]**	[23.29]**	[23.11]**	[22.74]**	[20.90]**
$Gender_i$	0.539	0.617	0.597	0.564	0.563
	[1.61]	[1.72]	[1.59]	[1.63]	[1.58]
PhD_i	−0.101	−0.114	−0.116	−0.104	−0.109
	[5.09]**	[5.36]**	[4.22]**	[5.23]**	[5.44]**
$Prof_i$	−0.039	0.104	0.143	−0.038	−0.019
	[0.21]	[0.56]	[0.73]	[0.20]	[0.10]
$Star_i$	0.719	0.672	0.699	0.625	0.61
	[2.28]*	[2.06]*	[2.04]*	[1.93]	[1.83]
Times $Cited_i$	0.051	0.066	0.029	0.077	0.087
	[0.38]	[0.46]	[0.19]	[0.56]	[0.61]
RAE_i	0.181	0.127	0.082	0.186	0.177
	[2.18]*	[1.45]	[0.86]	[2.19]*	[2.04]*
Dep $Size_i$	−0.210	−0.213	−0.219	−0.199	−0.18
	[1.76]	[1.71]	[1.65]	[1.62]	[1.43]
Constant	195.945***	222.048	225.483	203.269	213.03
	[39.874]	[5.19]**	[4.10]**	[5.06]**	[5.28]**
Observations	3649	3492	3335	3492	3335
Number of ind.	157	157	157	157	157

Time dummies and field dummies included.
All columns show negative binomial fixed effects results. Results in column (2) are for $Pyear_{it+1}$, results in column (3) are for $Pyear_{it+2}$. Similarly, results in column (4) are for $Pyear_{it-1}$, results in column (5) are for $Pyear_{it-2}$.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

evidence provides weak support for the findings in the literature that publishing performance drops by 15% 1 year before patenting (non-significant) and can drop by as much as 23% 2 years before patenting (a marginally significant result). Similarly, columns (4) and (5) in Table 5 show publishing activity 1 and 2 years respectively after patenting. In this case, we observe a 'jump' of 12% in productivity 1 year after patenting, although the result is not significantly different from zero. This jump in productivity is temporary as there is no evidence of persistence after 1 year.

4.2. Augmented results

Estimations of Model (1) do not provide strong evidence of either a crowding-in or a crowding-out effect related to patenting and publishing. This is interesting since it contradicts much previous evidence, mainly US based, of a linear complementarity between these activities. However, our model differs from many of those used in previous studies in that we focus simply on change of status from non-inventor to inventor. One possible explanation for our results is that the lack of correlation between patenting and publishing could be the result of a functional relationship between these two variables, which is more complex than is assumed in Eq. (1). The implicit assumption in model (1) is that the impact of patenting activity is homogeneous across inventors with different characteristics whereas we would expect to observe differences in this impact. For instance, model (1) rests on the particular assumption that the impact of patenting activity can be approximated by a simple step function. It does not matter how much an inventor patents: occasional and persistent inventors are treated in the same way. Also, it may be that the effects of patenting on publishing depend on the *intensity* of the patenting activity. In addition, publishing will likely depend on the scientific field of the researcher. In order to explore these hypotheses we model the impact of patenting as a function of an inventor's patenting experience and some other characteristics (Z_{it}). In other words, we estimate:

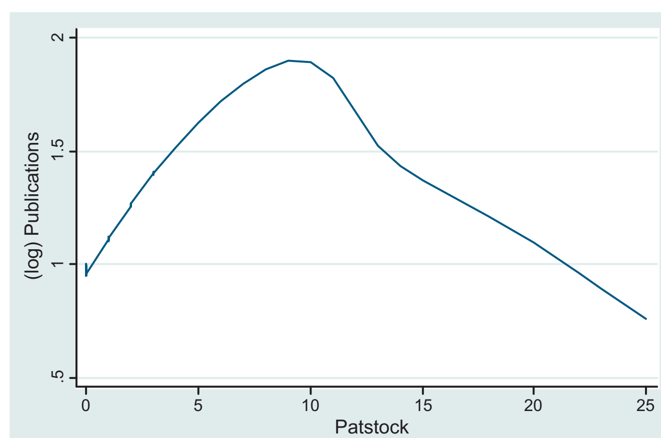

Fig. 1. Publications vs patent stock.

$$Y_{it} = X'_{it}\beta + \tau_0 P_{it} + \tau_1 (P_{it} x Z_{it}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (i = 1, \dots N \quad \text{and} \quad t = 1, \dots T) \qquad (2)$$

As a preliminary investigation of the relationship between patenting intensity and publishing, Fig. 1 plots the shape of the relationship between publications and (past) stock of patents using local linear regression methods.[14]

[14] Local Linear Regression is a nonparametric method that uncovers the relationship between two variables by running a series of regressions in a sequence of sub-samples each defined in the neighbourhood of each value of the explanatory variable (see Johnston and DiNardo, 1997).

Table 6
Descriptive statistics by size of patent portfolio (more vs less of 10 patents).

Variable	Definition	<10	≥10
$Gender_i$	Dummy if female	0.10	0.00
Age_{it}	Age	45	57
PhD_i	Year of PhD award	1985	1974
$Prof_i$	If professor at survey time	0.43	0.51
$Star_i$	Dummy if member of Royal Society	0.05	0.05
Times $Cited_{it}$	Average citations/paper/year	2.52	3.07
RAE_i	Department RAE score (2001)	4.92	5.00
Dep $Size_i$	Department size at survey time (log)	3.55	3.67
$Chemistry_i$	Dummy variable	0.35	0.51
$Physics_i$	Dummy variable	0.39	0.48
Computer $Science_i$	Dummy variable	0.15	0.00
$Engineering_i$	Dummy variable	0.10	0.00

The figure suggests a quadratic inverted U-shaped relationship between these variables. This is consistent with the results for US (Fabrizio and Di Minin, 2008) and Italian (Breschi et al., 2008) scientists and Larsen (2008) finds a curvilinear relationship for publication output and industrial collaborations in the case of Danish scientists. Publication performance grows up to a patent stock of 10, beyond this inflexion point, more patenting leads to fewer publications. Table 6 presents the main characteristics of the most prolific inventors (more than 9 patents). Despite some obvious characteristics, such as being older and holding a PhD for longer, highly productive inventors tend to be professors, receive more citations to their work, and work in larger and higher quality research departments. Also, they all work in Chemistry or Physics.

Table 7 presents the effects of patenting activity on publication intensity, controlling also for the scientific field in which the researcher is active. In columns (1) and (2) we replace the dummy for patenting activity with an interaction dummy given by the patenting dummy multiplied by experience, measured as the number of years after the first patent ($P_{it} \times \text{Exp}_{it}$). This variable (and its squared term) measures whether longer experience in patenting has an effect on scientific productivity. In both cases the results are not significantly different from zero. Columns (3) and (4) respectively replace the patenting dummy with the accumulated stock of patents and its square. The results for including the stock of patents linearly are not significantly different from zero. However, as shown in column (4), if we include a quadratic term for the stock of patents, a strong and significant 'inverted U-shaped' pattern emerges. This suggests that an increase in patenting activity intensity initially increases the number of publications up to a saturation point, after which more patenting reduces publication. The inflexion point is at about 10 patents. Note that this result is not driven by the researcher's age since we control for this variable (and its square) in the regression.[15] However, it should be noted also that although statistically significant, this result is based on a very small number of inventors with 10 or more patents (5 inventors or 14% of the inventors in our sample). Although their number is very small, these individuals account for 42% of the patents in our sample and therefore cannot be considered outliers. Consistent with information from company patents, a very small number of prolific inventors is responsible for an important share of total patenting output.

To check the robustness of the results, we investigate whether the curvilinear impact of patenting on publishing described above is biased by unobserved heterogeneity related to the quality of the scientist. In other words, if more talented inventors (the ones whose *average* papers receive the most citations) also patent more, then the variable patent stock (included in columns (3) and (4) in Table 7) could be capturing the effects of omitted ability or quality, rather than the pure incentive effects of patenting. In order to explore this possibility we interact the patenting dummy with the average number of citations per paper. The results are reported in column (5) where the citation variable is not statistically significant and the results for patent stocks hold.

Finally, we want to analyse whether the different characteristics of diverse scientific fields have an impact on the complementarity between patenting and publishing. In column (6) of Table 7 we interact our patenting dummy with scientific field. The results in Table 7 show that patenting has different effects depending on the scientific field: in Engineering and Computer Science it complements publishing, compared to Chemistry (and Physics although the variable is not significant) where we observe a crowding-out effect. The results by scientific field should be treated with caution, however, due to the small number of observations in Engineering and Computer Science. We could conjecture that the inverted U-shaped function identified in column (4) of Table 7 is capturing a scientific field effect.[16] According to the results in column (6), patenting has a negative effect on publishing in Chemistry so, as long as researches with a large stock of patents are concentrated in this field, which would be a reasonable expectation given the higher effectiveness and greater propensity to patent in this area, non-linear effect of publishing could be due to a field-specific effect. Unfortunately, we do not have enough degrees of freedom to explore whether the results from model (4) hold for each of the scientific fields because some fields have very few observations (see Table 2 for distribution of number of inventors by scientific field). However, it should be noted that in model (4) we control for fixed effects. If this is a valid approximation of 'true' fixed effects, our results should not be driven by field characteristics. Also, as shown in Table 6, in Physics there are inventors with high numbers of patents.

The results on the complementarity between patenting and publishing by UK scientists in the fields of Computer Science and Engineering confirm the positive relationship found for other countries. However, for Chemistry and Physics our evidence points to a substitution effect, or a threshold effect after which substitution between patenting and publishing sets in. These latter results are in line with the evidence presented by Calderini et al. (2009) for Italy, and Larsen (2008) for Denmark. Some evidence of a lack of compementarity in Physics is also reported by Stephan et al. (2007).

5. Impact of academic patenting on knowledge transfer

To assess the impact of academic patenting on knowledge transfer, we proceeded as follows. First, we considered the responses to our survey about the extent of engagement in a variety of interaction channels: (a) joint research agreements with industry; (b) contract research agreements; (c) consultancy work; (d) joint supervision of PhD students; and (e) equity interests in new companies (e.g. spin-offs). We constructed several dichotomous variables to assess whether a specific interaction channel was used in the period 2002–2003. We used logit regressions to examine the relationship between patenting and the probability of interacting through any of these channels.

Second, we computed our explanatory variable as the researcher's total accumulated patents for the period 1978–2001 (i.e. 'patent stock'), using data obtained by matching our 1528 survey respondents with the inventor information in patents granted

[15] The coefficients for age and age^2 are stable across all specifications and so are not affected by the way patenting experience is defined.

[16] We thank an anonymous referee for raising this point.

Table 7
Negative binomial regressions of publication counts (for different definitions of patenting activity).

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
P_{it}						−0.154** [0.078]
$P_{it} \times \text{Exp}_{it}$	−0.000 [0.006]	−0.011 [0.012]				
$P_{it} \times \text{Exps}^2_{it}$		0.001 [0.001]				
$P_{it} \times \text{Lstockpat}_{it}$			0.006 [0.010]	0.042** [0.019]	0.074*** [0.022]	
$P_{it} \times \text{Lstockpat}_{it}{}^2$				−0.002** [0.001]	−0.004*** [0.001]	
$P_{it} \times \text{Cited}_{it}$					−0.009 [0.008]	
$P_{it} \times \text{Cited}^2_{it}$					0.000 [0.000]	
$P_{it} \times \text{Physics}_{it}$						0.143 [0.127]
$P_{it} \times \text{Computer}_{it}$						0.858*** [0.321]
$P_{it} \times \text{Engineering}_{it}$						0.577** [0.226]
Age_{it}	0.215 [9.27]**	0.215 [9.34]**	0.194 [8.39]**	0.192 [8.37]**	0.191 [8.37]**	0.212 [9.23]**
Age^2_{it}	−0.003 [24.28]**	−0.003 [24.19]**	−0.003 [22.93]**	−0.003 [23.00]**	−0.003 [22.54]**	−0.003 [24.07]**
Gender_i	0.544 [1.63]	0.532 [1.59]	0.580 [1.68]	0.580 [1.69]	0.570 [1.65]	0.495 [1.50]
PhD_i	−0.100 [5.00]**	−0.102 [5.11]**	−0.105 [5.31]**	−0.106 [5.37]**	−0.110 [5.58]**	−0.102 [5.15]**
Prof_i	−0.033 [0.18]	−0.063 [0.34]	−0.041 [0.22]	−0.051 [0.28]	−0.094 [0.51]	−0.061 [0.34]
Star_i	0.705 [2.25]*	0.691 [2.21]*	0.715 [2.22]*	0.704 [2.18]*	0.815 [2.43]*	0.686 [2.19]*
Times Cited_i	0.053 [0.39]	0.061 [0.45]	0.074 [0.54]	0.082 [0.60]	0.094 [0.68]	0.012 [0.09]
RAE_i	0.179 [2.14]*	0.191 [2.26]*	0.188 [2.23]*	0.191 [2.27]*	0.193 [2.29]*	0.203 [2.44]*
Dep Size_i	−0.210 [1.75]	−0.222 [1.83]	−0.222 [1.82]	−0.234 [1.92]	−0.238 [1.93]	−0.235 [1.96]*
Constant	193.590*** [40.059]	198.456*** [40.154]	204.134*** [39.716]	206.126*** [39.636]	213.780*** [39.494]	198.353*** [39.813]
Observations	3649	3649	3540	3540	3540	3649
Number of ind.	157	157	157	157	157	157

Time dummies and field dummies included.
All columns show negative binomial fixed effects results.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

by the EPO (as explained in Section 3). To examine the impact of the intensity of patenting on current engagement in other technology transfer activities, we used the squared term of patent stock. This allows us to investigate the occurrence of non-linearity in the relationship between patent stock and the probability of engagement with business through a number of interaction channels.

Finally, we consider a set of individual and university department level control variables. Individual level characteristics include age of the researcher (and its squared term) and academic status (being a professor or not at the time of the survey). University level characteristics include a set of dummies to capture the department's ranking in the UK 2001 RAE (high = 5 and 5* scores, low = 4 or lower);[17] department size (measured as the average of full time equivalent staff in the period 1998–2001); and discipline dummies to capture the impact of a researcher being affiliated to any of nine scientific fields (with Physics as the reference category). Table 8 reports the results of our logistic regressions.

Table 8 shows that patent stock is positively correlated to the use of all the channels of interaction. However, it shows also that there is a threshold number of patents beyond which patenting is detrimental to the probability of interaction in joint research, contract research, consultancy with business and joint PhD training.[18] This inflexion point is reached at a stock of around eight patents for joint research agreements, contract and consultancy, and at close to seven patents for joint PhD training. As an example of the impact on joint research agreements of a discrete change in patenting, for a researcher with no previous engagement in patenting, a

[17] The RAE provides an assessment of the research quality of university departments, based mainly on peer review of the four best outputs of each researcher member of the department. In the 2001 RAE the overall evaluation of the department was expressed on a 7 grade scale from 1 (when almost none of the research output submitted for evaluation achieves national standards of excellence) to 5* (when a substantial proportion of the research outputs submitted for evaluation achieves international standards of excellence).

[18] Researchers may interact through more than one channel at the same time. Thus, our dependent variables are likely to be correlated. To properly account for the extent of this correlation we ran a multivariate probit regression on the probability of interaction for each channel. The results, which are available upon request from the corresponding author, confirmed our previous findings.

Table 8
Relationship between patenting and other mechanisms of knowledge transfer (Logit Regressions).

Variables	Joint Research	Contract Research	Consultancy	Joint PhD Training	Spin-offs
Patent stock	0.380***	0.412***	0.385***	0.381***	0.329***
	[0.107]	[0.101]	[0.108]	[0.094]	[0.096]
Patent stock^2	−0.025**	−0.026***	−0.025**	−0.029***	−0.011
	[0.011]	[0.008]	[0.012]	[0.010]	[0.008]
Age	0.063	0.055	0.043	0.113**	0.186**
	[0.053]	[0.054]	[0.057]	[0.055]	[0.089]
Age^2	−0.0008	−0.0007	−0.0006	−0.001**	−0.002**
	[0.0005]	[0.0006]	[0.0006]	[0.0005]	[0.0009]
Professorial status	0.860***	0.907***	0.896***	0.553***	0.648***
	[0.147]	[0.150]	[0.151]	[0.152]	[0.209]
RAE 2001 Low	0.148	0.254	0.371**	0.163	0.072
	[0.147]	[0.155]	[0.155]	[0.151]	[0.211]
RAE 2001 High	−0.030	−0.028	−0.044	−0.122	0.001
	[0.155]	[0.158]	[0.161]	[0.159]	[0.217]
Staff Dept. (ln)	0.016	−0.035	0.144	0.140	0.062
	[0.109]	[0.114]	[0.113]	[0.113]	[0.160]
Chem. Engineering	0.833**	1.869***	1.474***	1.004***	0.816*
	[0.331]	[0.356]	[0.314]	[0.326]	[0.491]
Chemistry	0.296	0.710***	0.571**	0.554**	0.411
	[0.208]	[0.214]	[0.227]	[0.215]	[0.358]
Civil Engineering	0.530*	1.295***	1.830***	0.541*	0.966**
	[0.280]	[0.287]	[0.296]	[0.292]	[0.440]
Computer Science	0.233	−0.013	0.039	−0.184	0.822**
	[0.237]	[0.254]	[0.271]	[0.266]	[0.380]
Electrical & Electronic	0.732***	1.377***	0.834***	0.724***	1.068***
	[0.226]	[0.237]	[0.246]	[0.234]	[0.348]
General Engineering	0.860***	1.177***	1.561***	0.849***	0.961**
	[0.262]	[0.261]	[0.271]	[0.266]	[0.398]
Mathematics	−1.452***	−0.962***	−0.599**	−0.979***	−0.765
	[0.281]	[0.270]	[0.289]	[0.297]	[0.507]
Mechanical, A.&M.	0.987***	1.735***	1.627***	1.034***	0.865**
	[0.228]	[0.245]	[0.242]	[0.231]	[0.361]
Metallurgy & Materials	0.947***	1.595***	1.650***	0.964***	0.769*
	[0.329]	[0.337]	[0.338]	[0.332]	[0.460]
Intercept	−2.192*	−2.255*	−3.106**	−4.200***	−7.668***
	[1.311]	[1.348]	[1.405]	[1.379]	[2.269]
N. observations	1447	1453	1455	1455	1453
Log Likelihood	−878.0	−841.2	−828.7	−844.0	−495.2
Wald χ^2 (17)	171.3***	253.9***	230.7***	142.8***	81.5***
Ps–R^2 (McKelvey & Zavoina)	0.22	0.27	0.24	0.17	0.19

Robust standard errors in brackets.
* Two tailed t-tests: $p < 0.10$.
** Two tailed t-tests: $p < 0.05$.
*** Two tailed t-tests: $p < 0.01$.

change from zero to one patent would increase the probability of engaging in joint research with business by 9% (holding all other variables at their means). However, for a researcher with a stock of 12 patents, having an additional patent would decrease the probability of engaging in joint research by 4% (holding all other variables at their means). Setting up a company (academic spin-off) is the only technology transfer activity where patenting has a positive and significant impact, with no statistically significant evidence of non-linear effects.

Table 8 shows also that age has a positive and significant impact only in the cases of joint PhD training and spin-offs, although again, above a certain threshold, there is a decreasing impact. Professorial status has a positive and significant impact on the probability of interaction, in all cases. If the academic researcher is a professor, then the probability of involvement in joint research agreements is 0.21 times greater than for an academic of lower academic status (holding all other variables at their means). With regard to departmental characteristics, the results show that being affiliated to top-ranked or larger departments has no significant impact on the probability to engage in any of the technology transfer channels examined. However, researchers in low-ranked departments are more likely to engage in consultancy work.

Our results show also that there are significant differences across disciplinary fields in terms of the probability of engaging in a particular type of knowledge transfer. Researchers in Engineering-related fields are generally more likely to engage in every type of interaction (compared to researchers in Physics), while researchers in Mathematics are generally less likely to be involved in knowledge-transfer activities with business.

Finally, as in the case of the relationship between academic patenting and publishing, it is important to note that the result of a curvilinear relationship is driven by a very small number of cases, since inventors with seven or more patents represent a small proportion of our whole sample of academics (just 19 cases or 7.6% of the inventors in our sample). However, as in the previous analysis, although there are very few prolific academics inventors, they account for 32% of the patents in our sample.

6. Conclusions

Several studies (using data from the US and Europe) have tried to assess the impact of increased academic patenting on publishing, and to a lesser extent on knowledge exchange with businesses. Very little systematic evidence is available for UK scientists. This paper has tried to fill this gap by examining a sample of UK scientists, in the Engineering and Physical sciences, based on two separate surveys of their activity in knowledge transfer, and the information from their CVs.

The first objective was to test for the presence of complementarity or of a substitution effect between patenting and publishing in the case of the UK. Our results indicate that academic patenting may be complementary to publishing at least up to a certain point (about 10 patents), after which we find evidence of a substitution effect (mainly in Chemistry and Physics). We also find weak evidence of a scientific field effect, with the most basic sciences (Physics and Chemistry) showing some evidence of a direct crowding-out effect while the Transfer or Pasteur's Quadrant Sciences (Computer Science and Engineering) show evidence of a crowding-in effect. The robustness of these results was checked by controlling for a large set of researcher characteristics and applying econometric techniques to control for heterogeneity and endogeneity.

The second objective was to examine the possible impact of increased academic patenting on engagement in knowledge transfer. In this case the results of our estimations support the existence of an inverted U-shaped relationship: the intensity of patenting is complementary to various channels of knowledge exchange with business up to a certain point (i.e. 7 or 8 patents, depending on the interaction channel), beyond which a substitution effect sets in.

Overall, our results cast doubt on the simplistic view of a complementary or substitution effect between academic patenting and knowledge diffusion channels (publishing and knowledge exchange with business). We find evidence that increasing the incentives for academics to patent may not be desirable above a certain level of patenting activity. In other words, more patenting may not always be good. If academic inventors (in the more traditional scientific fields such as Chemistry and Physics) become too involved in patenting, ultimately they publish less, and they also interact less intensively with companies via other channels. Interestingly, the thresholds we identify are quite similar for publishing and other channels of interaction with industry. In terms of a possible explanation for these results, we could speculate that academic scientists who become too involved in patenting activity may become distracted from (or devote less time to) other activities and focus mainly on the production of new knowledge that is patentable, and from which some financial return can be extracted. This interpretation seems consistent with the fact that we did not find any crowding-out effect between patent stock and spin-off activity.

A final observation for policy from the evidence presented here is that in this study on UK scientists, but also in the study by Calderini et al. (2009) for Italy and Stephan et al. (2007) for the US, the impact of patenting on academic researchers' activities seems to vary depending on the scientific field. In more basic/traditional disciplines, beyond a threshold level, higher levels of patenting are associated with lower productivity (in terms of publishing). A policy implication of these results is that, if we are interested in the scientific output of academic researchers, incentives for researchers should be set so that they do not create obstacles to those academics who are interested in a certain level of patenting activity, but also do not lead to an excessive focus on patenting. It should be stressed also that although the threshold effect was identified on the basis of a small number of prolific inventors, they are responsible for a substantial proportion of the patents, so their importance cannot be dismissed.

The literature on the economics of knowledge developed in the last 20 years emphasizes the difficulties inherent in the diffusion (distribution) of knowledge across actors. In the context of the university–industry complex, a variety of channels and approaches to knowledge transfer have emerged to maximize the exchange of knowledge in different scientific and technological contexts. Our results indicate that patenting (one of the most recent channels in term of development and one of the most incentivized in terms of policy) potentially can (we do not know whether or not the patents are used by anyone) act as another way to transfer knowledge from universities to the rest of society. However, we also find indications that beyond a certain threshold, a continuing focus on patenting can result in a negative effect on other channels of knowledge diffusion. As in the case of publishing (the traditional means of knowledge diffusion from academia), those researchers that are involved in some patenting activity are also involved in other forms of university–industry relationships, but those researchers that specialize in patenting seem to devote less attention to the other knowledge-exchange activities resulting, possibly, in an overall lower rate of transfer and subsequent utilization of knowledge.

Although interesting, our results require further corroboration and should be interpreted with caution given the nature of the databases used for the analysis. First, the starting sample may be biased in favor of those academics who interact with business (and therefore have a higher probability of being associated to a patent) as this type of interaction is more common in the scientific fields financed by the EPSRC compared to other scientific fields. Second, the first part of the analysis is based on a very detailed and unique dataset constructed from the information in researchers' CVs for the period 1975–2005. However, the sample could be biased as it includes only active academics, excluding older academics who may have been research-active during their careers but who were not engaged in EPSRC-funded research in the period surveyed. In our econometric analysis we control for the age of the academic to take account of this sample bias. Moreover, due to the complexities involved in data collection, the database includes only a small sample of researchers in four scientific fields (and a particularly small number in Computer Sciences and Engineering): larger samples are needed to validate our results. In addition, extracting comparable information from CVs is not easy, and we were not able to gather information on research funding during the 30-year period of our analysis. Lack of this control variable in our models may bias the result of complementarity if EPSRC funding (more oriented to publications) is correlated to industry funding (more oriented to patents), or if, more generally, more funding simply results in more research outputs (Antonelli, 2008). In either case, we should not interpret the co-occurrence between patenting and publishing as crowding in. Third, the second part of the analysis was based on a large database of academics but we analysed relationships only at the cross-sectional level. Further work is needed to test the robustness of the results with regard to the heterogeneity of scientists' characteristics, and the changes over time, and to control for problems related to endogeneity between patenting and the other channels of knowledge transfer. All these shortcomings call for some caution in the interpretation of our results.

Acknowledgments

The authors are grateful to Cristiano Antonelli, Stefano Breschi, Luigi Orsenigo, Paula Stephan and an anonymous referee for comments and suggestions. The paper has benefitted from the comments of participants of the CAS Workshop (Oslo), City University Seminar (London) and Bocconi CID Meeting (Milano). The authors are indebted to Oluwatosin Babalola, Silvia Maffioli and Ana Fernández Zubieta for their skilful database creation. Thanks are due also to Gianluca Tarasconi for providing data on patents granted by the European Patent Office. An earlier version of the paper was co-authored with Oluwatosin Babalola: we acknowledge her contribution to the current version of the paper. Financial support from the European Commission (FP6) Project, NEST-2006-PATH-Cul, CID, Contract No. FP6-043345 is gratefully acknowledged. Aldo Geuna acknowledges support from the International Centre for Economic Research (ICER), Turin (I)

Appendix A.

See Table A1.

Table A1
Distribution of researchers in the whole sample.

	Population surveyed	Valid responses	Response rate (%)
Chemical Engineering	174	62	35.6
Chemistry	754	271	35.9
Civil Engineering	242	86	35.5
Computer Science	536	162	30.2
Electrical & Electronic Engineering	496	172	34.7
General Engineering	292	116	39.7
Mathematics	563	216	38.4
Mechanical, Aero. & Manuf. Engineering	484	179	36.9
Metallurgy and Materials	201	69	34.3
Physics	595	195	32.8
Total	4337	1528	35.2

Appendix B. Dataset construction

B.1. ISI Web of Science database algorithm

1. Researchers' surnames and first initial only were entered in the general search section; this returns all authors with this name and first initial in the database. This was exported to the Endnote library.
2. The same procedure as in 1 but this time with first and second initials, and the results exported to a different Endnote library file. This double search procedure ensures that all researchers' publications were extracted from the web with minimal possibility of incorrect inclusion of authors. For example, a researcher Archer AP might be listed on a publication as Archer A or Archer AP so a search with Archer A* is unnecessary as this would return researchers with the same surname but with many other combinations of initials such as Archer AB, AD, etc.
3. The third search involved repeating steps 1 and 2 but including authors institutional addresses, noting address changes over time, which reduces the probability of incorrect inclusion of publications in the resulting data. All the results were exported to the same file.
4. The dataset resulting from (3) was crosschecked with CV publications lists, and incorrect inclusions eliminated from the file. In most cases, the list reflects researchers' publication lists almost entirely.
5. The data from (4) were compared with data from (1) and (2) following the elimination method used in (4).

Data were validated, line-by-line, taking account of co-authors, institutional affiliation at a particular point in time, and journal name.

B.2. Robustness of the cross sectional database

The consistence of the information in the two databases was analyzed to provide validation for the cross sectional database given the name matching procedure used. While 81% of cases were correctly matched, the proportion of mismatches is much higher among inventors than non-inventors. Indeed, among the scientists who, according to their CV information, were not involved in granted patents, we have an 89% correct match. However, among those who reported having been involved in granted patents, we were able to capture only 49%. Some of the difference are due to the fact that in the CV database a significant share of the inventors had only UK patents and also the CV database includes patent applications whose numbers are usually higher than granted patents. We examined whether our set of mismatched cases had particularly common or distinctive attributes. We observed no significant differences across scientific fields (in terms of the proportion of

Table A2
OLS linear regressions of (log 1 + publication counts).

Coefficient	(1)	(2)	(3)	(4)	(5)
P_{it}	0.205	0.129	0.134***	0.138	0.013
	[0.144]	[0.121]	[0.041]	[0.094]	[0.427]
Age_{it}	0.155***	0.117***	0.122***	0.171***	0.177***
	[0.013]	[0.013]	[0.009]	[0.011]	[0.010]
Agesqr_{it}	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
	[0.000]	[0.000]	[0.000]		
Gender_i		0.071	0.075		
		[0.109]	[0.093]		
PhD_i		−0.028***	−0.029***		
		[0.004]	[0.007]		
Prof_i		0.258***	0.250***		
		[0.079]	[0.069]		
Star_i		0.372*	0.339**		
		[0.217]	[0.135]		
Times Cited_i		0.090*	0.100**		
		[0.049]	[0.045]		
RAE_i		0.075*	0.060*		
		[0.040]	[0.031]		
Dep Size_i		−0.100*	−0.072		
		[0.059]	[0.044]		
Constant	−2.244***	54.368***	56.217***	−34.142	−18.469
	[0.246]	[8.805]	[13.857]	[2.076e+10]	[2.347e+11]
Observations	3649	3649	3649	3649	3540
R^2	0.44	0.53	.	0.67	
Number of idinv	157	157	157	157	157

Time dummies and field dummies included.
All the pooled regressions includes robust standard errors clustered on individuals in order to allow residuals to be correlated within each individual block. (1) Pooled regression, (2) Pooled regression, (3) Random Effects, (4) Fixed Effects, (5) Fixed Effects instrumental variables. Time fixed effects also included.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

mismatches). That is, there are no differences in the proportion of mismatches between Chemistry, Physics, Computer Science and Mechanical Engineering. We also observed no significant differences in relation to university affiliation. This is particularly important given that, because we used postcodes as our matching criterion, it could be expected that individuals affiliated to London-based universities were more likely to be under sampled. The proportion of mismatches for scientists affiliated to London-based universities, however, was not statistically significantly different from the proportion of those affiliated to non-London based universities.

Appendix C.

C.1. Model 1 robustness check

In order to test the robustness of our results we changed our regression technique to Ordinary Least Squares (OLS) (Table A2). Column (1) presents the results for OLS, controlling only for age, time dummies and field dummies. The result for patenting is positive (non-significant) and close to the figure in column 1 in Table A1. In column (2) we control for researcher characteristics and the coefficient for the patenting dummy drops, but remains non-significant. Column (3) estimates the linear model by random effects, which produces a similar coefficient to that in column (2), but the result is now significantly different from zero. Column (4) controls for individual unobserved heterogeneity by including a set of individual fixed effects: we consider this specification to be more consistent with the theoretical model because it assumes heterogeneity in the mean of the dependent variable. Column (4) shows that the results for the patenting dummy are not very different from those in the previous two columns, which suggests that individual observed variables approximate quite well to any other omitted characteristic. Finally, Column (5) shows the results of our estimation with instrumental variables. The coefficient for the patenting dummy drops and remains insignificant.

See Table A2.

References

Agrawal, A., 2006. Engaging the inventor: exploring licensing strategies for university inventions and the role of latent knowledge. Strategic Management Journal 27 (1), 63–79.

Agrawal, A., Henderson, R., 2002. Putting patents in context: exploring knowledge transfer from MIT. Management Science 48 (1), 44–60.

Amara, N., Landry, R., Idrissi, O., 2009. Patent applications and patent rates: evidence from Canadian researchers in engineering and natural sciences. Presented at the 7th Triple Helix Conference, 17–19 June 2009, Glasgow.

Antonelli, C., 2008. The new economics of the university: a knowledge governance approach. Journal of Technology Transfer 33, 1–22.

Azoulay, P., Ding, W., Stuart, T., 2007. The determinants of faculty patenting behavior: demographics or opportunities? Journal of Economic Behavior and Organization 63 (4), 599–623.

Banal-Estanol, A., Jofre-Bonet, M., Meissner, C., 2010. The Impact of Industry Collaboration on Research: Evidence from Engineering Academics in the UK. Working Paper 1190. Universitat Pompeu Fabra (UPF).

Bekkers, R., Bodas Freitas, I.M., 2008. Analysing knowledge transfer channels between universities and industry: to what degree do sectors also matter? Research Policy 37, 1837–1853.

Bhattacharjee, Y., 2006. Industry Shrinks Academic Support. Science 312, 671.

Blume, S., 1990. Transfer sciences: their conceptualisation, functions and assessment, presented to the conference. In: Consequences of the Technology Economy Programme for the Development of Indicators, Paris, 2nd–5th July.

Blumenthal, D., Campbell, E.G., Anderson, M.S., Causino, N., Louis, K.S., 1996. Withholding research results in academic life science: evidence from a National survey of faculty. Journal of the American Medical Association 277 (15), 1224–1228.

Breschi, S., Lissoni, F., Montobbio, F., 2008. University patenting and scientific productivity: a quantitative study of Italian academic inventors. European Management Review 5, 91–109.

Breschi, S., Lissoni, F., Montobbio, F., 2007. The scientific productivity of academic inventors: new evidence from Italian data. Economics of Innovation and New Technology 16 (2), 101–118.

Calderini, M., Franzoni, C., Vezzulli, A., 2009. Unequal Benefits of Academic Patenting for Science and Engineering Research. IEEE Transactions on Engineering Management 56 (February (1)), 20.

Campbell, E.G., Carridge, B.R., Gokhale, M., Berenhaum, L., Hilgartner, S., Holtzman, N.A., Blumenthal, D., 2002. Data withholding in academic genetics. Journal of the American Medial Association 287 (4), 473–480.

Carayol, N., 2007. Academic incentives, research organization and patenting at a large French University. Economics of Innovation and New Technology 16 (2), 119–138.

Cohen, W.M., Nelson, R.R., Walsh, J.P., 2002. Links and impacts: the influence of public research on industrial R&D. Management Science 48 (1), 1–23.

Crespi, G., Geuna, A., Verspagen, B., 2006. University IPRs and Knowledge Transfer. Is the IPR ownership model more efficient? SPRU Electronic Working Paper Series, Paper No. 154.

Dasgupta, P., David, P.A., 1987. Information disclosure and the economics of science and technology. In: Feiwei, G.R. (Ed.), Arrow and the Ascent of Economic Theory. New York University Press, New York.

Dasgupta, P., David, P.A., 1994. Towards a new economics of science. Research Policy 23 (5), 487–521.

Destler, B., 2008. A new relationship. Nature 453 (12), 853–854.

D'Este, P., Nesta, L., Patel, P., 2005. Analysis of University–Industry research Collaborations in the UK: Preliminary Results of a Survey of University Researchers, SPRU Report, May 2005, http://www.sussex.ac.uk/spru/documents/deste_report.pdf.

D'Este, P., Patel, P., 2007. University–industry linkages in the UK: What are the factors underlying the variety of interactions with industry? Research Policy 36 (9), 1295–1313.

Fabrizio, K., Di Minin, A., 2008. Commercializing the laboratory: faculty patenting and the open science environment. Research Policy 37, 914–931.

Florida, R., Cohen, W.M., 1999. Engine or infrastructure? The university role in economic development in Branscomb. In: Kodama, L.M., Florida, F.R. (Eds.), Industrializing Knowledge: University–Industry Linkages in Japan and the United States. London, MIT Press, pp. 589–610.

Geuna, A., Mowery, D. (Eds.), 2007. Special issue: production and dissemination of academic knowledge. Economics of Innovation and New Technology 16(2).

Geuna, A., Nesta, L., 2006. University patenting and its effects on academic research: the emerging European evidence. Research Policy 35 (6), 790–807.

Gewin, V., 2005. The technology trap. Nature 437 (13), 948–949.

Gulbrandsen, M., Smeby, J.C., 2005. Industry funding and university professors' research performance. Research Policy 34 (6), 932–950.

Hane, G., 1999. Comparing university–industry linkages in the United States and Japan. In: Branscomb, L.M., Kodama, F., Florida, R. (Eds.), Industrializing Knowledge: University–Industry Linkages in Japan and the United States. MIT Press, London, pp. 20–61.

Hausmann, J., Hall, B., Griliches, Z., 1984. Econometric models for count data with an application for the patent–R&D relationship. Econometrica 52 (4), 909–938.

HEFCE, 2006. Policy development Report on survey. Available: http://www.hefce.ac.uk/pubs/hefce/2006/06_25/.

Jensen, R., Thursby, M., 2001. Proofs and prototypes for sale: the licensing of university inventions. American Economic Review 91, 240–259.

Johnston, J., DiNardo, R., 1997. Econometric Methods. The McGraw-Hill Companies, Inc., Irvine.

Kenney, M., Patton, D., 2009. Reconsidering the Bayh–Dole Act and the current university invention ownership model. Research Policy 38 (9), 1407–1422.

Krimsky, J., 2003. Small gifts, conflicts of interest, and the zero-tolerance threshold in medicine. The American Journal of Bioethics 3 (3), 50–52.

Landry, R, Amara, N., Ouimet, M., 2007. Determinants of knowledge transfer: evidence from the Canadian university researchers in natural sciences and engineering. Journal of Technology Transfer 32, 561–592.

Larsen, M.T., 2008. To close for comfort? The Effect of University–Industry Collaborations on the Scientific Performance of University Professors, Mimeo.

Lissoni, F., Llerena, L., McKelvey, M., Sanditov, B., 2008. Academic patenting in Europe: new evidence from the KEINS database. Research Evaluation 16, 87–102.

Markiewicz, K.R., Di Minin, A., 2004. Commercializing the Laboratory: The Relationship Between Faculty Patenting and Publishing. Econ 222 /PHDBA 297-T: Seminar on Innovation, Haas School of Business.

Merton, R.K., 1968. The Matthew effect in science. Science 159, 56–63.

Mitroff, I., 1974. Norms and counter-norms in a select group of Apollo moon scientists. American Sociological Review 39, 579–595.

Mulkay, M., 1976. The mediating role of the scientific elite. Social Studies of Science 6, 445–470.

Murray, F., Stern, S., 2007. Do formal intellectual property rights hinder the free flow of scientific knowledge? Journal of Economic Behavior and Organization 63, 648–687.

Nelson, R.R., 2004. The market economy and the scientific commons. Research Policy 33 (3), 455–471.

NUBS (2003). UK University Commercialisation Survey: Financial Year 2002, AURIL-Nottingham University Business School (NUBS)-UNICO.

Perkmann, M., Walsh, K., 2008. How firms source knowledge from universities: partnering versus contracting. In: Bessant, J., Venables, T. (Eds.), Creating Wealth from Knowledge: Meeting the Innovation Challenge. Edward Elgar, Cheltenham, UK.

Shane, S., 2000. Prior knowledge and the discovery of entrepreneurial opportunities. Organization Science 11 (4), 448–469.

Siegel, D.S., Waldman, D.A., Atwater, L.E., Link, A.N., 2003. Commercial knowledge transfer from universities to firms: improving the effectiveness of university–industry Collaboration. The Journal of High Technology Management Research 14, 111–133.

Stephan, P.A., Gurmu, S., Sumell, A.J., Black, G., 2007. Who's patenting in the university? Evidence from a survey of doctorate recipients. Economics of Innovation and New Technology 16, 71-P 99.

Stern, S., 1995. Incentives and focus in university and industrial research: the case of synthetic insulin. In: Geligns, A., Rosenberg, N. (Eds.), The University–Industry Interface and Medical Innovation. Institute of Medicine, National Academy Press, Washington, DC.

Stokes, D.E., 1997. Pasteur's Quadrant: Basic Science and Technological Innovation. Brookings Institution Press, Washington, DC.

Thursby, J.G., Thursby, M.C., 2004. Are faculty critical? Their role in university–industry licensing. Contemporary Economic Policy 22, 162–178.

Thursby, J.G., Jensen, R., Thursby, M.C., 2001. Objectives, characteristics and outcomes of university licensing: a survey of major US universities. Journal of Technology Transfer 26, 59–72.

Valentin, F, Jensen, R.L., 2007. Effects on academia-industry Collaboration of extending university property rights. Journal of Technology Transfer 32, 251–276.

Wooldridge, J, 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press.