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Does working with industry come at a price? A study of doctoral candidates' performance in collaborative vs. non-collaborative Ph.D. projects

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ABSTRACT

Collaborative Ph.D. projects between university and industry constitute an important aspect of university–industry collaboration, yet has remained under-researched thus far. The specific question this paper asks is how collaborative Ph.D. projects perform compared to non-collaborative Ph.D. projects. Conducting an empirical study on 448 Ph.D. projects at Eindhoven University of Technology, it is observed that collaborative Ph.D. projects outperform non-collaborative Ph.D. projects both in terms of industrial performance (number of patents and patent citations) and academic performance (number of publications and publication citations). A further investigation indicates that the high performance of collaborative Ph.D. projects is specific to the university's collaborations with Philips and with Public Research Organisations. When measuring academic performance is a more restricted manner by looking at top-publications only, it is observed that collaborative Ph.D. projects no longer outperform non-collaborative Ph.D. projects. One of the policy implications of this study is that there seems to be no reasons for universities to be reserved to enter into collaborative Ph.D. projects, when such opportunities arise.

1. Introduction

Firms increasingly rely on external knowledge as a source of competitive advantage. One effect of this tendency is the increased rate of university–industry collaborations. Academic research is especially important for firms in science-based industries such as biotechnology and semiconductors, but also affects other industrial sectors (Ponds et al., 2007). At the same time, universities are also motivated to develop closer relationships with firms in order to gain access to research funds and firms' resources. What is more, universities are expected to contribute to their regional economy in terms of innovation and employment (the 'third mission'), and there is increasing political pressure on universities to do so (Geuna and Muscio, 2009).

There are different ways in which universities can transfer knowledge to industry, including contract research, collaborative research, patenting, and licensing (see Bekkers and Bodas Freitas, 2008; Gilsing et al., 2011, for a detailed discussion). While much of the earlier research on university–industry relations has focused on channels such as patenting and the role of technology transfer offices, some recent papers plea for greater attention to more interactive or collaborative modes, sometimes referred to as 'academic engagement' (D'Este and Patel, 2007; Perkmann et al., 2013). There are several reasons why firms are motivated to get involved in collaborations. First, in many knowledge areas, the tacit nature of knowledge necessitates actively working together with universities; second, through collaboration firms can co-develop knowledge that is relevant to the specific problems they face (Liebeskind et al., 1996; Ponds et al., 2007). Third, collaboration can provide access to critical resources such as skills, data and technology (Albors, 2002) as well as human capital (Lin and Bozeman, 2006). Finally, collaboration can improve partners' innovation capability and economic performance (Lööf and Broström, 2008).

Apart from the benefits of university–industry collaboration, industry involvement may also harm academic research as corporate interests may come to dominate public interests (Washburn, 2005). One particular concern about entering into such collaborations is the alleged trade-off between scientific and industrial relevance. The same reasoning may also apply for collaboration

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between university and Public Research Organisations (PROs). On the one hand, involving industry in collaboration can shift research towards narrow corporate interests (Nelson, 2004). On the other hand, collaboration with industry may improve research outcomes if both partners have complementary knowledge and converging interests (i.e. Gulbrandsen and Smeby, 2005). Empirically, however, the effect of a university's collaboration with industry or with PROs on its academic performance is still unclear as evidence of such effects is scarce (for a review, see Perkmann et al., 2013).

This study considers university–industry collaboration through joint Ph.D. projects. Almost one-third of all Ph.D. projects at Eindhoven University of Technology (the university where the underlying data is collected) are collaborative projects, making it a much more common phenomenon than university patenting, for instance. While collaborative Ph.D. projects have great potential for the transfer of knowledge between university and industry, they have received very little attention in the existing literature on university–industry relations. The particular research focus of this paper is whether collaborative Ph.D. projects have lower academic output than the more regular non-collaborative Ph.D. projects done "in-house" at the university. The aim of this paper, then, is to investigate the effect of industry collaboration on academic performance in the context of Ph.D. projects. To do so, an empirical study was conducted on 448 collaborative and non-collaborative Ph.D. projects at Eindhoven University of Technology, looking at actual differences in performance levels, and identifying the determinants of performance differences. The collaborative projects in this study include not only projects with firms, but also projects with Public Research Organisations (PROs), allowing a better understanding of performance differences specifically related to working with firms (opposed to those associated with PROs).

2. Literature review

An increasing number of industries rely heavily on science as an input for innovation. Electronics, pharmaceutics, biotech and nanotech are among the most important examples (Ponds et al., 2010). A key feature of science-based industries concerns the distributed nature of the innovation process. Given the complexity of the technologies involved, most of the innovations stem from inter-organisational collaboration rather than from projects carried out by single organisations. Following Powell et al. (1996), one can consider inter-organisational networks rather than single organisations as the prime 'locus of innovation'. Such collaborations typically involve both universities and industries, and in some cases other stakeholders as well. And, given the prime role of governments in steering and funding scientific research, government is often included as an actor as well. Indeed, science policy has shifted from a focus on basic research to one in which university–industry collaboration has become much more prominent. This development has become known as the "triple helix" of university–industry–government relations (Etzkowitz and Leydesdorff, 2000).

Even though for many universities – if not most – university patenting is much less common than joint knowledge production with industry, there is an extensive literature on university patenting and its potential trade-offs. Such studies range from the emergence of this phenomenon and its causes (e.g. Henderson et al., 1998; Mowery et al., 2001) to analyses of the total factor productivity of university licensing (Thursby and Thursby, 2002; Owen-Smith and Powell, 2003). A particularly fascinating aspect in this literature is the extent to which university patenting has detrimental effects on the rate, quality and direction of academic publications. This concern was initially prompted by a small-scale study by Murray and Stern (2007) suggesting that university patenting slowed down subsequent research on the same topic. That is, the authors identified a possible trade-off between academic patenting and scientific progress. Subsequent studies continued to look at this topic and consensus appeared, however, that there is no real trade-off between patenting and publishing. Azoulay et al. (2009) concluded that patenting has a positive effect on the rate of publications and a mildly positive effect on the quality of these publications. Looking at the field of nanotechnology, Meyer (2006) found that patenting scientists outperform their solely publishing (non-inventing) peers in terms of publication counts and citation frequency, though inventor-authors appear not to be among the most highly-cited authors in their category. Also other studies found robust complementarities between publishing and patenting (see for instance, Breschi et al., 2007; Fabrizio and Di Minin, 2008).

Yet, when it comes to university–industry collaboration, there are many more important considerations than the effect of patenting alone. Open issues remain, regarding teaching quality, open science and fundamental long-term research. Along those lines, Baldini (2008) discussed concerns such as: threats to scientific progress (disclosure and data sharing restrictions, the tragedy of the anti-commons, restrictions on research tools), changes in research (decline in patent quality, substitution between basic and applied research), threats to teaching activity (decline in teaching time, conflicts of interest, decline in student publications and informal learning) and threats to industry (restrictions on university–industry communication, delays to industry innovation, loss of proprietary information, obstacles to new research fields, unreasonable cost increases). In line with the context of this paper, the below will focus further on the effect of industry collaboration on the rate and quality of scientific output of academic scholars.

Making research outcomes public is one of the most challenging issues between university and industry (Etzkowitz and Leydesdorff, 2000; Salimi et al., 2014). Indeed, scholars are publication oriented and usually want to publish their research output as widely as possible. Furthermore, they have an incentive to publish their results quickly to increase their (citation) impact. However, industry aims to commercialise the knowledge its develops. Hence, generally speaking, firms have an incentive to appropriate their knowledge through secrecy, patenting or otherwise, rather than to disclose it through academic publications (Dasgupta and David, 1994; Blumenthal et al., 1996a). In case of collaboration, this may pre-empt publication of the research altogether, or result in publications that do not cover all research output. Alternatively, industry partners may want to delay the disclosure of the findings, so they have more time to commercialise the finding, or apply a patent (Blumenthal et al., 1996b; Nelson, 2004). As suggested above, such delays can result in lower (citation) impact of those publications.

Notwithstanding these plausible concerns about the effect of industry involvement on the rate of publication, the empirical evidence seems to provide little support to the proposition that industry involvement would lessen the incentive to publish. Gulbrandsen and Smeby (2005), for example, found a positive relationship between collaboration with industry and a high level of publications for Norwegian professors. Ponomariov and Boardman (2010) also found that faculties affiliated with a centre for industry collaboration were likely to have more publications than faculties not affiliated with such a place. Similarly, Abramo et al. (2009) found that university researchers who have collaboration with private sector have higher publications rate compared to their colleagues who are not involved in such collaboration. Regarding collaborative Ph.D. project as a specific form of collaboration, however, Lin and Bozeman (2006) found that Ph.D.

candidates having previous industry experience produce fewer publications over their entire career, while looking at the most recent scientific output (last 5 years), the authors could not find any significant difference.

Another line of arguments has focused on the effect of industry collaboration or industry involvement on the nature of the research findings and, more specifically, the academic quality and impact of that research. There are concerns that such an industry involvement shifts the researchers' agendas toward more applied topics rather than focusing on basic science (Perkmann et al., 2013) and that collaboration moves research towards narrow corporate interests. This could lead to a lower relevance for the academic audience and thus a lower impact of research. University researchers have a stronger incentive to impact on their peers, and, hence, are expected to put more effort in rendering their work relevant to their academic peers. By contrast, researchers working for firms and governments focus more on the production of applied knowledge in the light of the specific goals of their employer.

A number of studies have attempted to provide evidence on effect of industry involvement on the quality of academic output. They mostly do so by investigating the citation impact of publications (Hicks, 1995). A recent study of Frenken et al. (2010) investigated whether inter-university collaboration had a higher citation impact than university–industry or university–government collaboration. They tested this hypothesis for eight different fields of research, and found however that performance differences between inter-university collaboration and university–industry collaboration were rather small, and in some fields even non-existent. In a survey among U.S. faculty members and industry researchers on their collaborations, Lee (2000) found that both experienced benefits for their own research programmes. And, more recently, Wright et al. (2014) looked at over 12,000 inventions from the University of California. They found that corporate-sponsored inventions are cited and licensed more often than federally sponsored ones, which do not seem to suggest that corporate sponsoring leads to a more narrow research topic. Abramo et al. (2009), however, found that the impact factor of journals publishing academic articles co-authored by industry is generally lower than that concerning co-authorships with other entities (even though the publication rate of the first group is higher, as already discussed above).

One possible reason why most empirical studies do not find a lower publication rate or lower impact for industry-involved studies might be that collaborations serve as a valuable source for exploring and new ideas (Perkmann and Walsh, 2009). Positive effects may also be thanks to the exchange of complementary knowledge, as suggested by Banal-Estañol et al. (2011). Moreover, in collaborative projects, both partners can mutually benefit from each other's abilities in terms of specific (unique) skills and data as well as facilities and equipment – especially when there are unique facilities that very few organisations can afford.

While the findings of previous research on the (performance) effects of university–industry collaboration have been discussed this literature is still relatively scarce, and, as discussed above, also inconclusive at some points. Many of the existing papers also suffer from significant limitations. Firstly, many studies struggle with the fact that collaborations are usually quite diverse in nature. This makes it difficult to compare them, as well as difficult to compare them to non-collaborative research efforts. Second, many studies focus on collaborations that do not occur that often at any given institute, limiting the sample size such that statistical analysis are often not possible. These limitations have limited the current understanding of the effect of industry collaboration. Yet, at the same time, a better understanding of the causal relationship between engagement with industry and research performance is crucial for developing university policy and for designing policy interventions (Perkmann et al., 2013). This paper aims to overcome the above limitations by focusing on a relatively homogeneous type of university–industry collaborations, namely Ph.D. collaborations. Moreover, this approach allows for benchmarking with non-collaborative projects as well, allowing for a large enough data set to use statistical techniques to investigate the relation between collaborative efforts and academic performance.

3. Data and methodology

In order to investigate the academic performance of doctoral candidates, and to compare those who collaborated with industry with those who did not, bibliometric data was collected for former doctoral candidates at Eindhoven University of Technology in the Netherlands. The central unit of analysis was a doctoral candidate that had successfully completed a Ph.D. thesis, and data was collected concerning publications (including publication citation data) and patent data (including patent citation data) 4 years before the Ph.D. defence up to 7 years after the defence. Also a variety of other data was collected to use as control variables.

Preferring to collect data at one single university in order to reduce the variance stemming from differences between universities (e.g. arising from variance in institutional arrangements and settings), the Eindhoven University of Technology was chosen because of its extensive track record collaborating with industry in technological research. The university is based in the 'Brainport' region, which hosts many high-tech firms including Philips (a diversified, high-tech multinational), ASML (the world's leading firm in lithography for computer chip production), FEI (a leading specialist in transmission and scanning electron and ion microscopy) and NXP (a large semiconductor manufacturer). The intensive collaboration with industry, also reflected in a significant number of Ph.D. collaborations, allowing the construction of a database of sufficient size to address the central questions of this paper.

For this study, all 784 Ph.D. theses were investigated that were successfully defended at this university in the years 2000–2005. Theses were included from all different university departments being Applied Physics, Chemical Engineering and Chemistry, Electrical Engineering, Mathematics and Computer Science, Mechanical Engineering, as well as four departments involved in management and design. These are the departments of Built Environment, Biomedical Engineering, Industrial Design, and Industrial Engineering & Innovation Sciences (IE&IS). Because of the lower number of collaborations in these departments and the fact that they are more similar in nature (compared to the 'hard core' technical departments), these departments were grouped together in the analyses.

Based on the content of the summary and preface of these theses, a total of 89 collaborative Ph.D. projects with firms were identified. Another 135 collaborations with Public Research Organisations (PROs) were identified and included in the analyses because they can inform about performance differences specifically related to involving firms (e.g. possible effects of research being narrowed to corporate interests, or less complete disclosure) versus differences associated with PROs. This study, however, excludes collaborative projects with government institutions and those with other universities. In order to compare the 224 identified collaborative projects with regular, non-collaborative Ph.D. projects, 224 Ph.D. projects were selected that were not the result of any collaboration. While the methodology employed here does not require a matched sample, such matching was nevertheless performed in order to make descriptive statistics more informative. The matching was performed using the following criteria: university department, gender, nationality, and year of graduation (i.e. year of thesis defence). Extensive search through the literature in this field revealed only one other study that attempts to explain both the publication and patent output of former Ph.D. students (Buenstorf and Geissler, 2014). Different from this study, they did not look at university–industry collaboration, as they focused on the effect of the Ph.D. supervisor.

For performance data relating to the doctoral candidates' published works, this study restricts itself to publications in peer-reviewed journals. Following the findings of Kulkarni et al. (2009) on the coverage of peer-reviewed journals in various publication databases, the Elsevier's Scopus database was selected as the main source, and results were cross-checked with other sources (including CVs of the candidates themselves) to avoid both type I and type II errors. Data was selected on all papers in which the focal doctoral candidate was listed as author or co-author. To determine the impact of publications, this study relies on citation performance. An important decision here is whether self-citations are included or not. Some scholars believe that self-citations artificially inflate citations scores and the actual impact of papers (e.g. Glänzel, 2003). However, others hold the view that self-citation is a natural way for authors to strengthen their knowledge or idea (e.g. Hyland, 2003). All analyses for this study were performed both including and excluding self-citations. As will be shown below, the outcomes were similar in virtually all analyses.

For patent data, this study relied on the Thomson Reuters Derwent Innovations Index (DII)/Derwent World Patents Index (DWPI) database. The significant advantages are that this database comprises patent family information (thus preventing double-counts) and that patent metadata has been cleaned up and harmonised. All patent families were counted for which the doctoral candidates were listed as one of the inventors. Because this study aimed to observe events in the patent system that were as close as possible to the actual moment of invention, it uses the patent priority year for the timing of patents (the year in which the patent application was filed or, in the case of a patent that is part of a family, the year in which the first filing of a patent family member took place). For patent citations, each citation coming into the patent family is considered. To avoid double counting, multiple citations coming from one patent family into the focal patent family were treated as one.

For both the publication and the patent data, this study restricted its search to those published (or patents applied for) during the 4 years preceding the graduation year – the typical length of a Ph.D. project in the Netherlands – and the 7 years after the graduation year. As the doctoral candidates graduated between 2000 and 2005, the publication and patent observations span from 1996 to 2012. The final dataset includes a total of 4447 scientific publications and 861 patents.

In sum, in the analysis below, the word 'publication' refers to a peer reviewed publication as registered in Scopus with the focal doctoral candidate as author (or co-author); 'patent' means a patent family (as defined in the DII database) with the doctoral candidate listed as an inventor; 'Ph.D. project' means a doctoral research project that was successfully defended by the candidate. Furthermore, 'collaborative doctoral candidate' refers to a researcher who was involved as a Ph.D. candidate in a collaborative Ph.D. project with industry or with a PRO, and 'non-collaborative doctoral candidate' refers to a peer involved in a Ph.D. project that was not a collaboration at all.

3.1. Descriptive analysis

A first glimpse at the data underlying this study is provided in Table 1, showing the descriptive statistics comparing collaborative and non-collaborative doctoral candidates and using the 'moving' time window of 4+7 years as defined in the previous section. Doctoral candidates in collaborative projects are found to have a higher average number of publications. This is true both for collaborations with firms and for collaborations with PROs (which even score better). Collaborations also have a higher number of citations in total, but not per publication. Results are robust when including or excluding self-citations.

Table 2 shows descriptive information on the patenting performance for the doctoral researchers. Perhaps less surprisingly, collaborative doctoral candidates are more often listed as inventors on patents and receive more citations than their non-collaborative peers, both in total and per patent.

4. Main findings and discussion

Looking closer at the central research question, Section 4.1 starts by examining the relationship between the quantitative and qualitative performance of projects, including the question of whether there are trade-offs. Then Section 4.2 considers whether particular time patterns affect the findings on performance differences between the collaborative and non-collaborative doctoral candidates. In Section 4.3, a more detailed investigation is presented that distinguish not only between different types of collaboration, but also consider alternative explanations in an attempt to understand what actually causes performance differences. This final analysis is based on a series of regression analyses.

4.1. Publication and patent performance

One question that arose is whether there are trade-offs in terms of quantity (number of publications) and quality (here represented by citation impact), and whether these are different for candidates involved in collaborative versus non-collaborative Ph.D. projects. To analyse this, these two dimensions were plotted for all the individual candidates (Fig. 1). While the non-collaborative candidates strongly cluster in the lower left of the plot (few publications and low citation score), the collaborative candidates often do better in both dimensions. As such, the data does not suggest any of the above-mentioned types of trade-offs; also at individual candidate level, collaborative candidates combine higher publication performance and higher publication impact with some few exceptions. A similar analysis but excluding self-citations (not shown) yielded similar results.

A similar analysis was performed for patent impact, again considering the individual project level. The results are shown in Fig. 2. This data is more discrete in nature. As evidenced by Table 2, there are considerably fewer patent observations than publication observations – and many (often non-collaborative) projects overlap at the [0,0] coordinate of this graph. Nevertheless, there emerges a similar pattern as with publications: at individual level, collaborative doctoral candidates often combine a high performance in both dimensions.

4.2. Time profiles in publication and patent performance

As mentioned earlier, this paper focuses on Ph.D. projects that were finalised between the year 2000 and 2005, and is based on all associated publication and patent data for the Ph.D. candidates 4 years before and 7 years after the Ph.D. defence. The time dimension in data allows investigation into specific timing differences between collaborative and non-collaborative doctoral candidates. Do some result in early performance, while others only bear fruit in the longer term? Arguably, collaborative doctoral candidates are more likely to move to industry, and may

Table 1
Descriptive data concerning publication performance (from 4 years before to 7 years after graduation).

Groups	**Number of doctoral candidates**	**Number of publications**	**Mean number of publications per candidate**	**Total number of citations** (incl./excl. self-citations)	**Mean number of citations per candidate** (incl./excl. self-citations)	**Mean number of citations per publication** (incl./excl. self-citations)
Doctoral researchers in collaborative Ph.D. projects with firms	89	1105	12.42	11,274/9042	127/102	10.20/8.18
Doctoral researchers in collaborative Ph.D. projects with PROs	135	1554	11.51	18,849/14,603	140/108	12.13/9.40
Doctoral researchers not in collaborative Ph.D. projects	224	1788	7.98	25,005/18,856	112/84	13.98/10.55

Table 2
Descriptive data concerning patenting performance (from 4 years before to 7 years after graduation).

Groups	**Number of doctoral candidates**	**Number of patents**	**Mean number of patents per candidate**	**Total number of citations**	**Mean number of citations per candidate**	**Mean number of citations per patent**
Doctoral researchers in collaborative Ph.D. projects with firms	89	337	3.79	940	10.56	2.80
Doctoral researchers in collaborative Ph.D. projects with PROs	135	343	2.54	426	3.16	1.24
Doctoral researchers not in collaborative Ph.D. projects	224	181	.80	197	.88	1.09

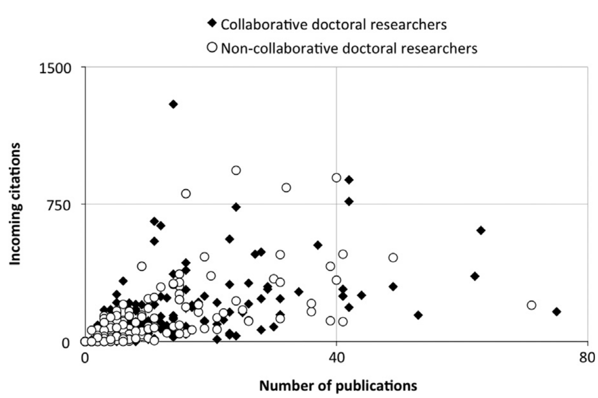

Fig. 1. Publications and forward citations per project (including self-citations).

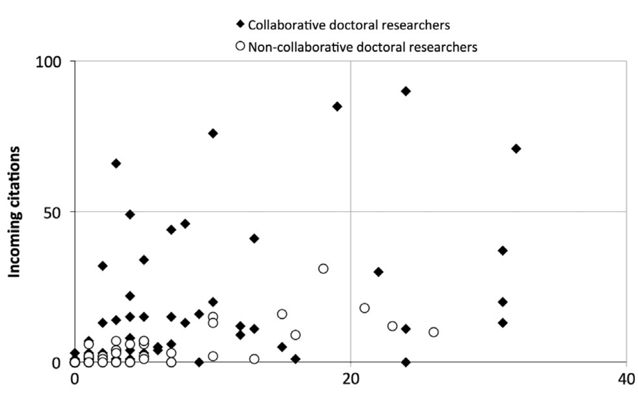

Fig. 2. Patents and forward patent citations per project.

consequently produce fewer publications than their counterparts who stayed in academia and used a postdoc period to get more papers out of their thesis research. Moreover, candidates aiming to stay in academia (read: mostly candidates in non-collaborative projects) might have stronger incentives to publish, as this is a key ticket for a career at a university.

Fig. 3, a, shows the average number of publications per project on an annual basis, where $t=0$ refers to the year in which the project was completed (i.e. when the thesis was defended). While both groups peak in their graduation year, it can be seen that collaborative doctoral candidates are consistently over-performing, both during project execution as well as after completion. Fig. 3, b, shows the citation performance. Also here, performance is consistently higher for collaborative doctoral candidates than for their counterparts, both during as well as after the project ended. While the data underlying this figure includes self-citations, similar outcomes were found when the authors' own citing papers were excluded from the analysis.

The patenting performance reveals patterns that are rather similar to those of the publication performance. Collaborative doctoral candidates consistently show a higher performance at any time (Fig. 4, a) and also incoming (forward) citations of these projects are higher at any time (Fig. 4, b). The peaks, however, are somehow different than those for publications. Collaborative doctoral candidates have a first patenting peak in their graduation year (presumably patents on inventions arising from the Ph.D. project), and a second peak at 4 years after project completion.

As discussed in Section 2, previous studies have focussed on the relationship between patenting and publications, and generally found no negative relationship, or even a positive one. In this study, collaborative doctoral candidates publish at a higher rate and patent more frequently, but the correlation between patenting and publishing rate very low ($-.024$) is not statistically significant (.613), which seems to indicate that the patenting rate neither diminishes nor enhances the publishing rate.

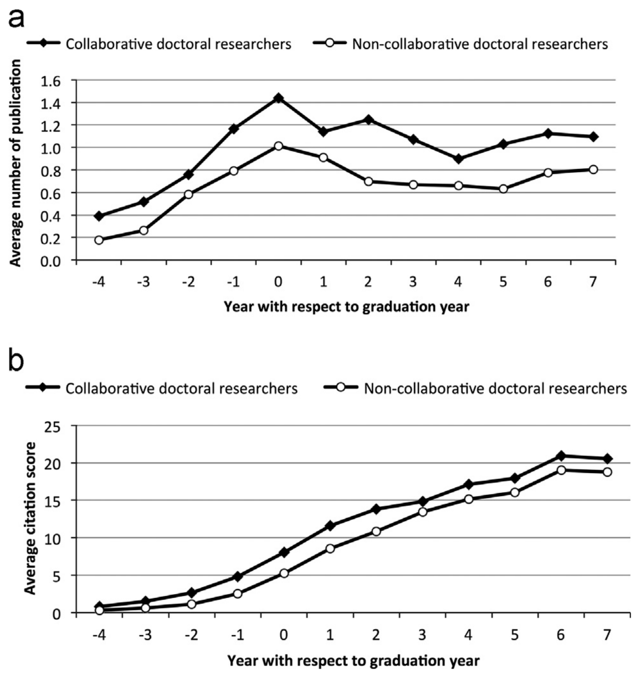

Fig. 3. Annual publication performance per project (a) and publication citation performance per project (b). Citations performance includes self-citations. For both figures, collaborations with firms and collaborations with PROs are combined into one category.

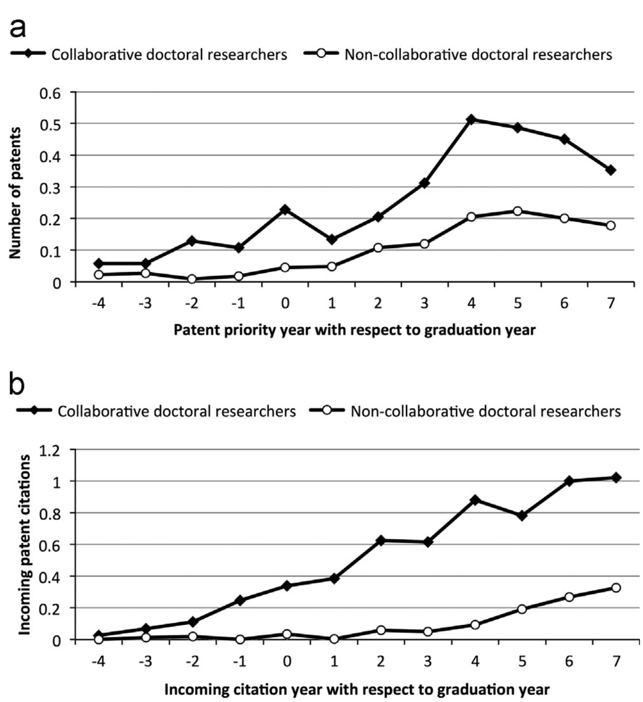

Fig. 4. Annual patent performance per project (a) and patent citation performance per project (b).

While clear results were derived on the high performance of collaborative Ph.D. doctoral candidates compared to their non-collaborative peers, it would be premature to conclude that collaborative projects do better than non-collaborative projects. Possibly, other factors affect project performance as well. Only by controlling for alternative explanations, the performance effect of collaborative versus non-collaborative projects can be more precisely assessed.

4.3. The determinants of performance differences

Moving beyond the mere observation that collaborative projects have higher performance, the coming sections are aiming to understand why. Is this higher performance an effect of the collaboration as such, or are there alternative explanations that account for the observed differences?

As explained above, the dataset used includes collaborations by Eindhoven University of Technology with firms as well as with PROs. This section will distinguish between the performance in these two categories of collaborative partners. Furthermore, the dataset of firm collaborations includes a considerable number of projects conducted in collaboration with Philips, a very large multinational firm that was originally established in Eindhoven, the same city as in which the university is located at which the data was collected. Philips is known for its long-standing academic culture, fostering a large research organisation that is still located in this city (Boersma, 2002). To investigate whether this firm is different from other firms with respect to the performance of its collaborations with Eindhoven University of Technology, these collaborations were analysed separately.

To better understand to what degree the observed differences are indeed an effect of collaboration, a number of alternative explanations was considered. Firstly, the disciplinary nature of the project was considered. Possibly, collaborative projects are over-represented in disciplines with higher publication and patenting rates as well as higher citation rates. By considering the department in which the project was executed, differences in publication propensity between academic fields can be corrected for. As discussed in the data section, the doctoral candidates in the data set came from Applied Physics, Chemical Engineering and Chemistry, Electrical Engineering, Mathematics and Computer Science, Mechanical Engineering, as well as four departments involved in management and design. Secondly, the nationality of doctoral candidate was considered. Thirdly, the candidate's gender was taken into account. Finally, it was considered whether the supervisor at the university was a ‘star scientist’. Such supervisors do not only attract more talented Ph.D. candidates, but they may also improve the performance of their students through tacit knowledge transfer and reputational effects (Buenstorf and Geissler, 2014). What is more, star-scientists may collaborate more often with industry, and, if so, may partially explain the high performance of collaborative projects. For this study, ‘star scientists’ are identified as all university supervisors who authored over 200 publications in peer-reviewed journals listed in Elsevier's Scopus database in 2013. Out of the 224 doctoral researchers who worked on collaborative projects, 70 candidates (i.e. 31%) were supervised by a total of 20 star scientists. Of the 224 doctoral candidates who did not work on collaborative projects, 55 (i.e. 25%) were supervised by a total of 21 star scientists. These statistics indicate the large share of Ph.D. projects with high-performing supervisors.

The analysis presented in this section is based on a series of negative binomial regression given that the dependent variables (publication, patents, citations) are all count variables (Frenken et al., 2005). In addition, a binary logit regression models was applied to analyse who ever published a top-ten highest-cited paper. The different types of collaborations as well as the additional determinants of performance are entered as independent variables. Details on the correlation among independent variables can be found in Table A1 in Appendix A. The correlation table shows that none of the variables are highly correlated.

Table 3 shows the results concerning academic publication performance. Starting with the publication quantity (‘total publications’), Model 1 shows that performance for both firm and PRO collaborations is significantly higher than for doctoral candidates not involved in a collaborative project. However, if the collaborations between Philips

Table 3
Determinants of doctoral candidates' academic publication performance.

Dependent variable→	Total publications[a]				Total citations (including self-citation)[a]			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Collaboration with firm	**.442***** (**.1310**)				.126 (.1258)			
Collaboration with Philips		**.815***** (**.1950**)	**.755***** (**.2130**)	**.589***** (**.2131**)		.111 (.1897)	**.602***** (**.2133**)	.209 (.2059)
Collaboration with firm other than Philips		.149 (.1564)	.070 (.1581)	.066 (.1586)		.135 (.1489)	−.008 (.1527)	.045 (.1528)
Collaboration with PRO	**.366***** (**.1143**)	**.366***** (**.1143**)	**.401***** (**.1162**)	**.429***** (**.1166**)	**.224**** (**.1094**)	**.224**** (**.1094**)	**.512***** (**.1147**)	**.626***** (**.1129**)
Electrical Engineering[c]			.034 (.1852)	.223 (.1856)			**−1.005***** (**.1835**)	**−.561***** (**.1788**)
Applied Physics[c]			−.071 (.1378)	.067 (.1400)			**−.812***** (**.1376**)	**−.446***** (**.1382**)
Mechanical Engineering[c]			**−.289*** (**.1634**)	**−.436***** (**.1664**)			**−1.021***** (**.1577**)	**−1.306***** (**.1580**)
Mathematics and Computer Science[c]			**−.712***** (**.1827**)	**−.422**** (**.1890**)			**−2.270***** (**.1795**)	**−1.590***** (**.1837**)
Management and Design[c]			**−.624***** (**.2063**)	**−.481**** (**.2075**)			**−1.034***** (**.2033**)	**−.996***** (**.1963**)
Candidate is Dutch			−.080 (.1099)	−.059 (.1099)			**.293***** (**.1103**)	**.273**** (**.1084**)
Candidate is male			**.248*** (**.1354**)	**.276**** (**.1350**)			**.394***** (**.1361**)	**.484***** (**.1317**)
University supervisor is star scientist				**.625***** (**.1218**)				**1.263***** (**.1184**)

Dependent variable→	Total citations (excluding self-citation)[a]				10 per cent of highest cited papers[b]			
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
Collaboration with firm	.188 (.1260)				−.604 (.512)			
Collaboration with Philips		.108 (.1900)	**.690***** (**.2156**)	.287 (.2070)		−.051 (.647)	.073 (.680)	−.140 (.697)
Collaboration with firm other than Philips		.230 (.1491)	.089 (.1542)	.192 (.1544)		−1.097 (.754)	**−1.260*** (**.763**)	−1.215 (.765)
Collaboration with PRO	**.251**** (**.1095**)	**.251**** (**.1095**)	**.606***** (**.1161**)	**.737***** (**.1144**)	.280 (.343)	.280 (.343)	.225 (.356)	.185 (.361)
Electrical Engineering[c]			**−1.070***** (**.1845**)	**−.611***** (**.1792**)			−.680 (.612)	−.403 (.631)
Applied Physics[c]			**−.983***** (**.1394**)	**−.602***** (**.1395**)			−.186 (.388)	−.042 (.399)
Mechanical Engineering[c]			**−1.087***** (**.1582**)	**−1.352***** (**.1580**)			**−1.359**** (**.651**)	**−1.503**** (**.658**)
Mathematics and Computer Science[c]			**−2.371***** (**.1791**)	**−1.666***** (**.1831**)			**−.492*** (**.776**)	−1.077 (.799)
Management and Design[c]			**−1.068***** (**.2034**)	**−1.027***** (**.1966**)			−1.207 (.779)	−1.049 (.785)
Candidate is Dutch			**.331***** (**.1121**)	**.321***** (**.1100**)			.276 (.379)	.326 (.381)
Candidate is male			**.490***** (**.1353**)	**.541***** (**.1306**)			.378 (.472)	.324 (.475)
University supervisor is star scientist				**1.302***** (**.1182**)				**.865**** (**.353**)

Notes: Standard Error is shown in parentheses. Any value with a significance level of 10% or lower is printed in bold.

* 10% significance level.
** 5% significance level.
*** 1% significance level.
[a] Negative binomial regressions; dependent variable measured in −4 to +7 time window.
[b] Binary logit regressions; dependent variable measured in −4 to +7 time window.
[c] Baseline is the Department of Chemical Engineering and Chemistry, the largest department in terms of collaborations in our dataset.

and those with other firms are separated (Model 2), it becomes clear that the effect for companies can be solely contributed to the Philips collaborations. Apparently, the long academic culture in this company leads to high publication performance (and possibly also the preference of talented doctoral candidates or the best university supervisors to work with this company). Doctoral candidates who worked with other companies do not have a significantly higher number of publications than their non-collaborating peers – but it is relevant to stress that their performance is not significantly lower either. Adding controls for academic disciplines (Model 3) reveals some significant results: the departments of Mechanical Engineering, Mathematics and Computer Science, and the four management or design departments have a lower performance than the Department of Chemical Engineering and Chemistry, the largest department and baseline. Nevertheless, the earlier positive effects of collaborations remain stable. Finally, and less surprisingly, adding a control for star scientists (Model 4) shows that the supervision by these prolific publishers has a significant positive effect on publication output. The earlier positive effects of collaboration remain stable (Interestingly, the lower coefficients suggest that Philips works more often with star scientists than with others).

Models 5–8 in Table 3 show the results for citation impact of publications. Collaborations with Philips have a higher impact, but this effect disappears once star scientists are controlled for. Collaborations with PROs also have a higher impact, and this effect remains once star scientists are included. Collaborations with firms other than Philips have a publication quality comparable to their non-collaborative peers, not significantly better but also not significantly worse. Models 9–12 present the same analysis as Models 5–8 but exclude self-citations; the results are very similar.

Up to this point, all the presented analyses were about performance aspects of the full set of papers published by the studied Ph.D. candidates. It may also be interesting, however, to investigate the effect on top-level papers, i.e. 'break-through' papers that can have a long-lasting effect on the research field. Even if the *average* performance of collaborations may be better or similar to non-collaborations, this does not yet tell whether it is these collaborations that produce the real break-through papers. To the contrary, in-house university projects could arguably outperform collaborative projects in this respect, as in-house university projects might be more focused on fundamental and high-risk research questions, whereas collaborative projects might more focus on applied and low-risk topics (where the feasibility of having research outcomes is relatively high). To investigate this further, a series of analysis was performed that only consider at break-through papers, which is here defined as a paper in the top-10 per cent highest-cited papers published in a given year in the data set. The results are shown in Models 13–16 in Table 3, where the dependent variable is whether the Ph.D. candidate has produced a break-through paper. From the descriptive analysis in Table 1, it was already seen that the mean citation rate *per publication* was higher for non-collaborative projects than for collaborative projects. The results in Model 15 show that in-house university projects (non-collaborative Ph.D. projects) do have some advantage since highly cited papers are less likely when collaborating with firm (except with Philips). This finding is in line with Meyer (2006) who found that university professors who patent, tend to outperform their peers in terms of citations, but not so if looking at the highest-cited publications. This suggests that scientific breakthroughs, as indicated by highly-cited publications, tend to result from in-house Ph.D. projects rather than from collaborative projects. However, when all control variables are entered (Model 16), in-house no longer significantly differ from collaborative projects, and instead the only statistically significant explanation of being in the 10% best cited papers is whether a university star scientist was involved.

Table 4 presents the same analysis, but now for patents. Again, both the quantity (the total number of patents by the doctoral candidate) and the impact (proxied by the forward citation score of the patents) are considered. The effect of collaboration on patenting is much stronger than on publishing, which is in line with expectations since collaboration partners have stronger incentives to get patents from their research than universities. All types of collaborations (with Philips, with firms other than Philips and with PROs) perform significantly better, both in quality and impact. Adding alternative determinants does not change any of these significant effects.

5. Conclusions, limitations and policy implications

By focusing on collaborative Ph.D. projects, this study investigated a relatively large and homogeneous series of university–industry collaborations, allows the use of statistical techniques to derive findings on how such collaborations differ in performance form university-only projects. This study shows that doctoral candidates involved in collaborative Ph.D. projects achieve a higher performance than non-collaborative Ph.D. projects with respect to several performance dimensions, including the number of publications, the number of citations to these publications, the number of patents, and the number of forward citations to these patents. This superior performance remains in the years following the graduation of the candidates graduate. While the overall impact (citation performance) of doctoral candidates involved in collaborative Ph.D. projects is higher than that of their non-collaborative peers, the impact *per publication* is somewhat lower, because the increase in number of papers is somewhat higher than the increase in received citations.

In sum, the results show that there is no dimension in which collaborative projects perform worse than non-collaborative projects, and in several ways they perform significantly better.

A deeper investigation of the determinants of this improved performance revealed that this firstly depend on the nature of the collaborative partner. Secondly, the numerous collaborations with Philips, a firm with a long academic culture, displayed a higher performance, as well as Ph.D. projects with PROs. Collaborations with other firms, however, showed no significant performance differences with non-collaborative peers: they were not significantly better (but not significantly worse either). Thirdly, university supervision by a 'star scientist' makes a notable difference, but generally did not alter the significance of the other determinants. When a more restrictive notion of impact is used by zooming in on the ten per cent highest-cited publications – as an indication of a scientific breakthrough, collaborative projects no longer outperform non-collaborative projects. But they do not perform worse either. In sum, the findings suggest that working with industry or PROs is not helpful – but neither harmful – to yield scientific breakthroughs.

Our study contributes to the ongoing debate of the possible trade-offs between industry involvement and academic performance. A better understanding of the causal relationship between engagement with industry and research performance is crucial for developing university policy and for designing policy interventions (Perkmann et al., 2013). Yet, earlier studies had not been conclusive to this end, and suffered from some limitations. The results of this study suggest that the complementarities in university–industry Ph.D. projects (in terms of resources and expertise) outweigh the alleged downsides of industry involvement in jeopardising the academic quality of research. Hence, from a public policy point of view, there seems little reason to discontinue the current schemes that support collaborative Ph.D. projects.

Table 4
Determinants of doctoral researchers' patenting performance.

Dependent variable→	Total patents				Total citations to patents			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Collaboration with firm	**1.14***** **(.1496)**				**2.301***** **(.1449)**			
Collaboration with Philips		**1.709***** **(.2100)**	**1.641***** **(.2171)**	**1.627***** **(.2211)**		**2.912***** **(.2038)**	**2.825***** **(.2255)**	**2.806***** **(.2269)**
Collaboration with firm other than Philips		**.590***** **(.1838)**	**.658***** **(.1949)**	**.665***** **(.1959)**		**1.659***** **(.1714)**	**1.612***** **(.1914)**	**1.647***** **(.1940)**
Collaboration with PRO	**.746***** **(.1360)**	**.746***** **(.1360)**	**.789***** **(.1521)**	**.781***** **(.1537)**	**1.093***** **(.1358)**	**1.093***** **(.1358)**	**1.416***** **(.1628)**	**1.411***** **(.1630)**
Electrical Engineering[a]			**.340*** **(.2054)**	**.352*** **(.2085)**			**1.113***** **(.2099)**	**1.150***** **(.2132)**
Applied Physics[a]			.032 (.1711)	.030 (.1712)			−.025 (.1754)	−.042 (.1761)
Mechanical Engineering[a]			−.287 (.2006)	−.300 (.2041)			−.052 (.2035)	−.092 (.2060)
Mathematics and Computer Science[a]			.104 (.2187)	.121 (.2241)			**.420*** **(.2266)**	**.473**** **(.2314)**
Management and Design[a]			**−.799***** **(.2754)**	**−.790***** **(.2762)**			**−.568*** **(.2908)**	**−.542*** **(.2909)**
Candidate is Dutch			**.479***** **(.1418)**	**.486***** **(.1430)**			**1.310***** **(.1545)**	**1.363***** **(.1613)**
Candidate is male			**.676***** **(.1820)**	**.677***** **(.1819)**			**.467**** **(.1861)**	**.484**** **(.1869)**
University supervisor is star scientist				.053 (.1513)				.185 (.1569)

Notes: Negative binomial regressions; dependent variable measured in −4 to +7 time window. Standard Error is shown in parentheses. Any value with a significance level of 10% or lower is printed in bold.

* 10% significance level.
** 5% significance level.
*** 1% significance level.
[a] Baseline is the Department of Chemical Engineering and Chemistry, the largest department in terms of collaborations in our dataset.

An important question is to what degree the findings of this study results are generalisable. Two aspects of the setting in which the data was collected are important here. Firstly, there is a strong geographic dimension to university–industry collaboration (Ponds et al., 2007). The Eindhoven region hosts many innovative companies in science-based industries, including world-leading companies as Philips, ASML and NXP. The analysis has shown that such firm characteristics are associated with increased university–industry collaboration performance. Hence, the findings may well apply to universities in regions with highly innovative firms, but may not be generalisable to universities located in regions with less innovative firms. Secondly, as already noted, Dutch Public Research Organisations (PROs) are predominantly commercially oriented as they are largely depend on contract research. Whether the findings can be generalised to other countries where PROs play different roles, remains an empirical question. Given that the presented research design can be readily replicated, more studies can be done on the topic of joint Ph.D. projects in other regional and national contexts. On a final note, while the specific context of Eindhoven University of Technology may have impacted the findings of this study, the authors were not aware of specific policies or practices at the university – or its departments – that influence the findings. In fact, earlier studies have not found large differences between this university and its peers (Bekkers and Bodas Freitas, 2008; Gilsing et al., 2011).

An important methodological limitation of this study is that causal effect of industry involvement on output performance were established. Indeed, the positive effects found may largely or even solely be due to self-selection by candidates, where the brighter and more motivated candidates opt more often to work in collaborative Ph.D. projects compared to other candidates. Indeed, such self-selection effects may be presented as a collaborative Ph.D. projects offer an additional reward upon completion: collaboration with industry provides the Ph.D. candidate with an additional career option as (s)he can easily enter both academia and industry afterwards. Hence, on average, the brighter candidates may be drawn more often to Ph.D. projects with industry. To some extent, this was controlled for talent by taking into account star-scientists. One can expect that brighter candidates are more drawn to star-scientists. Hence, though very imperfect, the star-scientists dummy not only proxies the university supervisor's talent, but also – at least to some extent – the candidate's talent. Yet, in a future research design, one would ideally collect data on the quality of a Ph.D. candidate before (s)he enters a Ph.D. project as to be able to control for self-selection effects properly (cf. Baruffaldi et al., 2012).

Note, however, that from the perspective of a university the possible self-selection of talented candidates into collaborative projects should actually be encouraged. Indeed, having industry (or a PRO) being involved in Ph.D. projects may be a way to attract

Table A1
Correlation between independent variables.

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Collaboration with firm (1)											
Collaboration with Philips (2)	.557§										
Collaboration with firm other than Philips (3)	.767§	−.106$^{\#}$									
Collaboration with PRO (4)	−.327§	−.182§	−.251§								
Electrical Engineering (5)	.199§	.220§	.068	−.165§							
Applied Physics (6)	−.064	.014	−.088*	.134§	−.217§						
Mechanical Engineering (7)	−.096$^{\#}$	−.115$^{\#}$	−.026	.098$^{\#}$	−.152§	−.246§					
Mathematics and Computer Science (8)	−.006	.062	−.055	−.086*	−.214§	−.133§	−.151§				
Management and Design (9)	.010	−.150§	.128§	−.019	−.224§	−.362§	−.254§	−.222§			
Candidate is Dutch (10)	−.005	.036	−.034	−.033	−.038	.077	.047	−.028	−.067		
Candidate is male (11)	.053	.000	.063	.016	.052	.036	.006	−.058	−.002	.135$^{\#}$	
University supervisor is star scientist (12)	−.023	.021	−.043	.101$^{\#}$	−.050	−.050	.233§	−.225§	.134	−.067	.018

Phi coefficient was used to measure the association between dichotomous variables.

* $p < .10$.
$^{\#}$ $p < .05$.
§ $p < .01$.

talented Ph.D. candidates, who would otherwise leave academia altogether. Also, it may help to attract candidates who were already working in industry and for which the company is willing to finance the Ph.D. project in return for a collaborative project. Without providing opportunities for collaborative projects, some of these candidates may never do a Ph.D. project at all.

Whatever the exact causes of the higher performance Ph.D.'s engaged in collaborative projects, the main policy conclusion still holds: this study does not indicate grounds for concerns by universities (and agencies funding collaborative Ph.D. projects) that the involvement of industry or PROs decrease academic output. Collaborative projects do not have a lower performance, and in many cases even a significantly higher performance. Moreover, much attention has recently been focused on the role of university not only as a knowledge producer, but also as a generator of more commercial spillovers (Audretsch and Lehmann, 2005). That is, knowledge spillovers, commercialisation and ultimately economic growth as the main parts of university policy, can be fostered and facilitated by collaboration with industry. Hence, the university can be advised to continue industry collaborations, as well as collaborations with PROs as no reasons were found to be reserved to enter into such collaborations when such opportunities arise. Taking the particularly positive effects of Philips collaborations in mind, universities could also put particular emphasis on entering into collaborations with firms or institutes with a long-standing academic/research tradition, rather than firms less experienced in performing research themselves. One could think of firms that have been having institutionalised research labs for a long time, and/or firms whose research staff has been proliferate in publications in academic journals.

Appendix A

See Table A1.

References

Abramo, G., D'Angelo, C.A., Di Costa, F., Solazzi, M., 2009. University–industry collaboration in Italy: a bibliometric examination. Technovation 29 (6–7), 498–507.

Albors, J., 2002. Networking and technology transfer in the Spanish ceramic tiles cluster: its role in the sector competitiveness. J. Technol. Transf. 27 (3), 263–273.

Audretsch, D.B., Lehmann, E.E., 2005. Do University policies make a difference? Res. Policy 34 (3), 343–347.

Azoulay, P., Ding, W., Stuart, T., 2009. The impact of academic patenting on the rate, quality and direction of (public) research output. J. Ind. Econ. 57 (4), 637–676.

Baldini, N., 2008. Negative effects of university patenting: myths and grounded evidence. Scientometrics 75 (2), 289–311.

Banal-Estañol, A., Stadler, I.M., Castrillo, J.D.P., 2011. Research output from university–industry collaborative projects. Econ. Dev. Q. 27 (1), 71–81.

Baruffaldi, S., Conti, A., Visentin, F., 2012. Social Proximity and Payoffs: An Application to Ph.D. Student Productivity Student Productivity. Working paper. Available from 〈http://www.tiger.gatech.edu/REER%202012%20Papers/Baruffaldi_Conti_Visentin.pdf〉.

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

Blumenthal, D., Campbell, E.G., Causino, N., Louis, K.S., 1996a. Participation of life-science faculty in research relationships with industry. N. Engl. J. Med. 335 (23), 1734–1739.

Blumenthal, D., Campbell, E.G., Causino, N., Louis, K.S., 1996b. Relationships between academic institutions and industry in the life sciences—an industry survey. N. Engl. J. Med. 334 (6), 368–374.

Boersma, F.K., 2002. Inventing Structures for Industrial Research. A History of the Philips Nat. Lab., 1914–1946 (Doctoral thesis). Aksant Academic Publishers, Amsterdam.

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

Buenstorf, G., Geissler, M., 2014. "Like Doktorvater, like son?" Tracing role model learning in the evolution of German laser research. J. Econ. Stat. (Jahrb. Nationaloekon. Stat.) 234 (2–3), 158–184.

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

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

Etzkowitz, H., Leydesdorff, L., 2000. The dynamics of innovation: from National Systems and "Mode 2" to a Triple Helix of university–industry–government relations. Res. Policy 29 (2), 109–123.

Fabrizio, K.R., Di Minin, A., 2008. Commercializing the laboratory: faculty patenting and the open science environment. Res. Policy 37 (5), 914–931.

Frenken, K., Hölzl, W., de Vor, F., 2005. The citation impact of research collaborations: the case of European biotechnology and applied microbiology (1988–2002). J. Eng. Technol. Manag. 22 (1), 9–30.

Frenken, K., Ponds, R., Van Oort, F., 2010. The citation impact of research collaboration in science-based industries: a spatial-institutional analysis. Pap. Reg. Sci. 89 (2), 351–371.

Geuna, A., Muscio, A., 2009. The governance of university knowledge transfer: a critical review of the literature. Minerva 47 (1), 93–114.

Gilsing, V., Bekkers, R., Bodas Freitas, I.M., van der Steen, M., 2011. Differences in technology transfer between science-based and development-based industries: transfer mechanisms and barriers. Technovation 31 (12), 638–647.

Glänzel, W., 2003. Bibliometrics as a Research Field: A Course on Theory and Application of Bibliometric Indicators. Retrieved 07.04.14 from 〈http://www.cin.ufpe.br/~ajhol/futuro/references/01%23_Bibliometrics_Module_KUL_BIBLIOMETRICS%20AS%20A%20RESEARCH%20FIELD.pdf〉.

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

Henderson, R., Jaffe, A.B., Trajtenberg, M., 1998. Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988. Rev. Econ. Stat. 80, 119–127.

Hicks, D., 1995. Published papers, tacit competencies and corporate management of the public/private character of knowledge. Ind. Corp. Change 4 (2), 401–424.

Hyland, K., 2003. Self-citation and self-reference: credibility and promotion in academic publication. J. Am. Soc. Inf. Sci. Technol. 54 (3), 251–259.
Kulkarni, A.V., Aziz, B., Shams, I., Busse, J.W., 2009. Comparisons of citations in Web of Science, Scopus, and Google Scholar for articles published in general medical journals. J. Am. Med. Assoc. 302 (10), 1092–1096.
Lee, Y., 2000. The sustainability of university–industry research collaboration: an empirical assessment. J. Technol. Transf. 25 (2), 111–133.
Liebeskind, J.P., Oliver, A.L., Zucker, L., Brewer, M., 1996. Social networks, learning, and flexibility: sourcing scientific knowledge in new biotechnology firms. Organ. Sci. 7 (4), 428–443.
Lin, M.-W., Bozeman, B., 2006. Researchers' industry experience and productivity in university–industry research centers: a "scientific and technical human capital" explanation. J. Technol. Transf. 31 (2), 269–290.
Lööf, H., Broström, A., 2008. Does knowledge diffusion between university and industry increase innovativeness? J. Technol. Transf. 33 (1), 73–90.
Meyer, M., 2006. Are patenting scientists the better scholars? An exploratory comparison of inventor-authors with their non-inventing peers in nano-science and technology. Res. Policy 35 (10), 1646–1662.
Mowery, D.C., Nelson, R.R., Sampat, B.N., Ziedonis, A.A., 2001. The growth of patenting and licensing by US universities: an assessment of the effects of the Bayh–Dole act of 1980. Res. Policy 30 (1), 99–119.
Murray, F., Stern, S., 2007. Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. J. Econ. Behav. Organ. 63 (4), 648–687.
Nelson, R.R., 2004. The market economy, and the scientific commons. Res. Policy 33 (3), 455–471.
Owen-Smith, J., Powell, W.W., 2003. The expanding role of university patenting in the life sciences: assessing the importance of experience and connectivity. Res. Policy 32 (9), 1695–1711.
Perkmann, M., Walsh, K., 2009. The two faces of collaboration: impacts of university–industry relations on public research. Ind. Corp. Change 18 (6), 1033–1065.
Perkmann, M., Tartari, V., Mckelvey, M., Autio, E., Broström, A., D'este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Krabel, S., Kitson, M., Llerena, P., Lissoni, F., Salter, A., Sobrero, M., 2013. Academic engagement and commercialisation: a review of the literature on university–industry relations. Res. Policy 42 (2), 423–442.
Ponds, R., van Oort, F., Frenken, K., 2007. The geographical and institutional proximity of research collaboration. Pap. Reg. Sci. 86 (3), 423–443.
Ponds, R., Van Oort, F., Frenken, K., 2010. Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. J. Econ. Geogr. 10 (2), 231–255.
Ponomariov, B.L., Boardman, P.C., 2010. Influencing scientists' collaboration and productivity patterns through new institutions: university research centers and scientific and technical human capital. Res. Policy 39 (5), 613–624.
Powell, W.W., Koput, K.W., Smith-Doerr, L., 1996. Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. Adm. Sci. Q. 41 (1), 116–145.
Salimi, N., Bekkers, R., Frenken, K., 2014. Governance mode choice in collaborative Ph.D. projects. J. Technol. Transf. , http://dx.doi.org/10.1007/s10961-014-9368-5 (published online 19.09.14).
Thursby, J., Thursby, M., 2002. Sources of growth in university licensing. Manag. Sci. 48 (1), 90–104.
Washburn, J., 2005. The Corporate Corruption of American Higher Education. Basic Books, New York.
Wright, B.D., Drivas, K., Lei, Z., Merrill, S.A., 2014. Industry-funded academic inventions boost innovation. Nature 507 (7492), 297–299.