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The effect of academic consulting on research performance: evidence from five Spanish universities

Francesco Rentocchini
University of Trento
Department of Economics
francesco.rentocchini@economia.unitn.it

Liney Manjarrés - Henríquez
Polytechnic University of Valencia
INGENIO [CSIC-UPV]
limanhe1@ingenio.upv.es

Pablo D'Este
Polytechnic University of Valencia
INGENIO (CSIC-UPV)
pdeste@ingenio.upv.es

Rosa Grimaldi
University of Bologna
Department of Management
rosa.grimaldi@unibo.it

Abstract

This paper investigates whether engagement in consulting activities has a significant impact on the research performance of academic scientists. The study relies on a sample of 1743 individual faculty, from five Spanish

universities, who have been recipients of publicly funded grants or have been principal investigators in activities contracted by external agents over the period 1999-2004. Our findings show that engaging in consulting activities has an overall negative impact on the average number of ISI-publications. However, the effect of consulting on the scientific productivity of academic scientists varies across scientific fields: academic consulting is found to have a negative impact only in the field of ?Natural and Exact? sciences, while in all other scientific fields, we do not find any significant impact of academic consulting on scientific productivity.

The effect of academic consulting on research performance: evidence from five Spanish universities

Francesco Rentocchini[ac#], Liney Manjarrés-Henrìquez[a] , Pablo D'Este[a], Rosa Grimaldi[b]

[a] INGENIO [CSIC-UPV], Polytechnic University of Valencia, Spain
[b] Department of Management, University of Bologna, Italy
[c] Department of Economics, University of Trento, Italy

Abstract

This paper investigates whether engagement in consulting activities has a significant impact on the research performance of academic scientists. The study relies on a sample of 2678 individual faculty, from five Spanish universities, who have been recipients of publicly funded grants or have been principal investigators in activities contracted by external agents over the period 1999-2004. By implementing a propensity score matching estimator method, we show that engaging in consulting activities has an overall negative impact on the average number of ISI-publications. However, the effect of consulting on the scientific productivity of academic scientists depends on the scientific fields and the intensity of engagement in consulting activities. Academic consulting is found to have a negative impact in the fields of 'Natural and Exact Sciences' and 'Engineering', but not in the case of 'Social Sciences and Humanities'. When the intensity of consulting activity is taken into account at the discipline level, engaging in consulting activities has an overall negative impact on scientific productivity only for high levels of involvement in consulting activities, but not for moderate ones.

[#] Corresponding author: Department of Economics, Faculty of Economics, via Inama 5, I-38122, Trento, Italy, e-mail: francesco.rentocchini@economia.unitn.it, Tel: 0039 0461 882162, Fax: 0039 0461 882222

1. INTRODUCTION

The engagement of scientists in knowledge and technology transfer activities is a topic that has attracted an increasing amount of interest in the last years, both among scholars and policy makers. Governments worldwide have been calling for greater interaction between universities and industry, under the rationale that this interaction is instrumental to foster technological development and economic achievements (OECD, 2003; DIUS, 2008; Dutrenit and Arza, 2010) and to strengthen the co-evolution between scientific and commercial opportunities (Rosenberg & Nelson, 1994; Veugelers & Cassiman, 2005). At the same time, sceptics have raised concerns about a possible negative impact that universities' involvement in technology transfer can have on the production and advancement of scientific knowledge/production (Krimsky, 2003).

Studies looking at the impact of universities' involvement in knowledge and technology transfer on scientific productivity have focused on a limited set of mechanisms of technology transfer, mostly including patents and academic spin-offs (Agrawal and Henderson, 2002; Azoulay et al., 2009; Toole and Czarnitzki, 2010), and to a lesser extent research collaborations (Gulbrandsen and Smeby, 2005; Lee and Bozeman, 2005). Whilst these specific forms of academic entrepreneurship and transfer of intellectual property represent economically relevant mechanisms of technology transfer, the importance, volume and impact on scientific production of the overall external engagement activities by scientists might be underestimated as a result of neglecting other forms of university-industry technology transfer, encompassing consulting, joint publications, staff exchange and joint student supervision, which have received less attention in the literature (Schartinger et al., 2002; D'Este and Patel, 2007).

Moving from these premises, this paper focuses on one of these less traceable and often informal mechanisms of external engagement by scientists, represented by academic consulting. In our view the current lack of systematic analysis of academic consulting is particularly unfortunate because academic consulting is a comparatively more frequent phenomenon than other means of engagement in knowledge transfer activities by academic scientists (i.e. patents, spin-offs or joint research collaborations); it is often a critical channel through which university research impacts on industrial R&D (Cohen et al., 2002; Arvanitis et al., 2008; Bekkers and Bodas-Freitas, 2008); and it is also appreciable as a stream of income for university in general, and for academic scientists in particular (Perkmann and Walsh, 2008).

Drawing upon the above discussion, this study investigates whether the engagement in consulting activities has an impact on the research performance of academic scientists. To investigate this, we rely on a sample of 2678 individual faculty, from the five universities of the Valencian Higher Education system, who have been recipients of publicly funded grants or have been principal investigators in R&D contracts over the period 1999-2004.

Our findings show that engaging in consulting activities has an overall negative impact on the average number of ISI-publications in the subsequent period. However, the effect of consulting on the scientific productivity of academic scientists varies across different scientific fields and for different levels of intensity in consulting activities. Academic consulting is found to have a negative impact in the fields of Natural and Exact Sciences and Engineering, but not in the case of Social Sciences and Humanities. When the intensity of consulting activity is taken into account (within each of these disciplines), engaging in consulting activities has an overall negative impact on scientific productivity only for high levels of involvement in consulting activities, but not for moderate ones.

The paper is structured as follows. Section 2 reviews the relevant literature and puts forward the main research questions of this study; Section 3 describes the data used in the analysis, while Section 4 provides an explanation of the methodology. Section 5 presents the results and Section 6 concludes.

2. LITERATURE BACKGROUND

This section provides a brief overview of the literature that investigates the relationship between knowledge transfer activities and scientific performance, and it discusses the conflicting arguments regarding the impact of academic consulting on scientific productivity.

2.1 Knowledge transfer activities and scientific productivity: an overview

The impact of knowledge transfer activities on research performance has become a key area of concern for both scholars and policy makers interested in assessing the social and economic impact of the engagement of university scientists with non-academic communities. Despite the increasing amount of empirical evidence regarding the impact on research productivity of academic entrepreneurial behavior, in particular, and knowledge transfer, more generally, the extant literature remains quite inconclusive, providing mixed findings which reflect different views in an ongoing open debate.

At one end of the spectrum there are advocates of universities' involvement in technology transfer who welcome scientists' engagement in knowledge transfer activities, arguing that closer contacts between industrial and academic research will bring benefits to both industrialists and academic researchers. The underlying rationale for this argument is that interaction with the private sector provides scientists with important learning and financial opportunities, thus inducing a complementary effect between the time spent on research and time spent on public-private interaction. In particular, involvement in knowledge transfer provides a setting in which academic researchers might identify new and relevant research topics, take advantage of competences and infrastructure available in firms; and benefit from financial pay-offs of successful commercialization of research products (Van Looy et al., 2006; Breschi et al., 2007; Buenstorf, 2009).

On the other hand, sceptics hold that the dramatic growth in academic patenting and licensing that has occurred over the last two decades has raised several concerns about the potentially negative effects that the commercialization of scientific discoveries could have on the conduct of academic researchers. In particular, it has been argued that financial incentives from patenting and licensing could shift the orientation of scientists away from basic and towards applied research, and could also undermine their commitment to the norms of open science, thereby leading to undesirable behaviors, such as data withholding, secrecy and publication delays (Blumenthal et al., 1996; Krimsky, 2003; Link & Scott, 2003).

From an empirical point of view, there are several contributions that have addressed this issue drawing mostly upon data on academic patenting and engagement in spin-off activities, reaching conflicting conclusions. Fabrizio and DiMinin (2008) and Stephan et al. (2007) have found a statistically positive effect of researchers' patenting on publication counts. Findings by Breschi et al (2007; 2008) reveal that academic inventors tend to publish more and produce higher quality papers than their non-patenting colleagues, and increase further their productivity after patenting. The beneficial effect of patenting on publication rates last longer for serial inventors, that is, academic inventors with more than one patent.

There are also findings in support of negative effects, portraying a tradeoff between patenting and the progress of academic science. Surveys of academic scientists have suggested that patenting skews scientists' research agendas toward commercial priorities, causes delay in the public

dissemination of research findings and crowds out efforts devoted to research (Blumenthal et al., 1996; Campbell et al., 2002; Krimsky, 2003). The main argument in this case is centered on the idea that research and entrepreneurial activities are competing for researcher's limited time and thus a substitution effect is in place between time dedicated to develop new research ideas and time spent in commercializing these ideas. In line with this argument, Calderini et al. (2009) find evidence of a substitution effect between patenting and publishing when publications in basic sciences are taken into account. Buenstorf (2009) in a study based on academic spin-offs finds that, in the long run, founding a spin-off may be detrimental to the quantity and quality of a researcher's output. In the same vein, Toole and Czarnitzki (2010) highlight the existence of a significant decrease in the research performance of American academic scientists when they start working on commercialization through the creation of for-profit firms.

Finally, some studies have suggested the existence of a curvilinear relationship between the extent of engagement in knowledge transfer activities and research productivity. For instance, Crespi et al. (2011) suggest that academic patenting is complementary to publishing at least up to a certain level of patenting output after which there is evidence of a substitution effect. While, looking at softer forms of engagement such as research collaboration and contract research with industry, Manjarres-Henriquez et al. (2009) and Larsen (2008) find that complementarities with research productivity exist only for moderate levels of knowledge transfer engagement.

2.2 Scientists' engagement in consulting activities and scientific productivity
Studies looking at the relationship between academic consulting and research performance are rare when compared to the attention placed on other forms of knowledge transfer activities such as patenting, spin-off activities or joint-research partnerships. This is unfortunate because academic consultancy is a channel of knowledge transfer that deserves thoughtful consideration on its own right for at least the following three reasons.

First, academic consulting is a widespread phenomenon. Compared to other means of engagement in knowledge transfer activities by academic scientists, such as patents and spin-offs, consultancy exhibits a much higher prevalence among university researchers. Indeed, involvement in consultancy is not the prerogative of academics in certain scientific disciplines, but an activity that is prevalent across many scientific fields (Bird and Allen, 1989; Louis et al., 1989; D'Este and Patel, 2007; Landry et al., 2010). Even though the figures on the proportion of academic scientists involved in consulting differ across studies, ranging from 18% (Bozeman and Gaughan, 2007), to

31% (Gulbrandsen and Smeby, 2007) or 38% (D'Este and Perkmann, 2010), academic consulting is systematically reported among the most frequent channels of interaction with non-academic communities.

Second, as several studies have revealed, academic consulting is often a critical channel in the process of knowledge and technology transfer between university and industry. As Cohen et al. (2002), Arvanitis et al. (2008) and Bekkers and Bodas-Freitas (2008) show, consulting is a key channel through which university research impacts on industrial R&D. Similarly, Thursby et al. (2001) have shown that the large majority of licensed inventions from university research requires inventors' assistance for being successfully commercialized. Finally, consulting activity is also appreciable as a stream of income for university in general, and academic scientists in particular. For example, academic researchers in the UK earned, on average, an extra of 2458 GBP in 2006 thanks to consulting activities, an order of magnitude similar to the source of funding from R&D contracts with industry, and consistently above the figures accounted by royalty income from licenses or spin-offs (Perkmann and Walsh, 2008).

Given the high rate of occurrence of academic consulting, it is reasonable to raise questions about its impact on scientific performance, in a similar vein as it has been done for other forms of knowledge transfer. Even though scholars have under-investigated the subject (some notable exceptions being Boyer and Lewis, 1984; Rebne, 1989; Mitchell and Rebne, 1995 and Perkmann and Walsh, 2008), it is possible to identify arguments anticipating a positive impact of consulting on scientific productivity, as well as arguments in support of a negative impact of academic consulting on scientific productivity. We discuss the basis for these two contentions below.

On one hand, academic consulting can be research enhancing, opening new ideas and insights for research that could far outweigh the time and efforts devoted to problem solving activities committed by the scientists in consultancy work. Following Azoulay et al. (2009) in their discussion on the potential complementarities between patenting and publishing, it is possible to argue along similar lines with regards to the potential complementarities between academic consulting and publishing. In this sense, academic consulting can reinforce the research activities of the academic scientists for the following reasons. First, consulting activities may be direct byproducts of research activities, as in the cases in which joint research activities require the active assistance of academics to industrialists' requirements (Mansfield, 1995; Thursby et al., 2001). Second, academic consultancy may be an additional source of funding for the laboratory or

department of the consulting scientist and contribute to the research agenda of the university department. Third, academic consulting might help making acquaintances with researchers in companies, making the scientist visible to new constituencies and intertwine with new research networks that might become sources of ideas for new research projects (Azoulay et al., 2009).

This latter type of consulting would fit the 'research-driven' mode suggested by Perkmann and Walsh (2008), which is generally characterized by medium to long-term commitments between the academic scientists and their clients, and would generally involve access to data drawn from industrial processes or information on problems and challenges from large, science and technology-intensive firms.

On the other hand, much of the discussion on academic consulting rests on the perception that time spent on consulting detracts from dedication to the primary roles of teaching and research (Mitchell and Rebne, 1995). In this sense, it is argued that there is a trade-off between consulting and research activities because devoting time to consulting comes at the expense of efforts oriented to basic research. This rationale is congruent with one type of consultancy that has been suggested by Perkmann and Walsh (2008): 'opportunity-driven' consultancy. According to Perkmann and Walsh, opportunity-drive consultancy is mainly articulated as a form of income augmentation on the side of the academic scientist, who is basically motivated into consultancy as a response to personal income opportunities. This type of academic consulting is further characterized by the mobilization of already existing expertise by the scientists involved in consulting, and a low level of commitment with regards to the interaction with the client (i.e. short term contracts). The rationale here is that, while these contractual arrangements can provide additional sources of personal income for the scientists, these contracts are not necessarily complementary with academic research, and may actually be counterproductive if they detract a significant amount of time from research activities.

Finally, the literature has suggested a number of factors that provide further structure to the relationship between academic consulting and scientific productivity. One such factor relates to the moderating role of the field of science. In certain scientific fields academic consulting might be particularly well-aligned with academic research agendas, compared to other fields. For instance, in engineering-related fields of science, academic consulting can be quite complementary with research activities insofar as it increases the exposure of scientists to new contexts of application of research and to areas of commercially useful inquiry that can spur insightful ideas for research. Conversely, in more fundamental fields of science, these complementarities might be less obvious

or infrequent. Perkmann and Walsh (2008) suggest that much of the research-driven consultancy is likely to be found in Pasteur-type fields of science, where considerations of fundamental understanding are combined with consideration of practical use in setting research agendas.

In short, even though academic consulting plays an important part as a mechanism of knowledge transfer, there is a paucity of research on this subject. Our work aims at filling this gap by investigating whether engaging in consulting has a significant impact (either positive or negative) on the scientists' research productivity.

3. DATA SOURCES

3.1. Data

The main source of information used in this investigation was provided by the technology and transfer offices of the five public universities of the Valencian Higher Education system: University of Alicante (UA), Miguel Hernández University (UMH), Jaume I University (UJI), University of Valencia (UV) and the Polytechnic University of Valencia (UPV). Except for the University of Valencia, all other universities have been created in the last 40 years. The data are analysed at the individual faculty level. Our sample consists of 2678 research active faculty – that is, academics who have been recipients of publicly funded grants or principal investigators in R&D contracts over the period 1999-2004. This figure accounts for approximately 20% of the entire population of faculty in these five universities in 2004.

Our faculty sample is distributed across the five universities considered in this study, as follows: 43% at UV; 24% UPV; 15% UA; 9% UJI; and 9% UMH (a distribution that is largely identical to that corresponding to the entire faculty population across the five universities). One of the value added features of this data is that it provides detailed information on the specific type of research projects and contracts in which academic researchers have been involved over the period 1999-2004. This includes project level information for both publicly funded research projects and contractual arrangements with third-parties, either industry or public administration. One of the contractual arrangements for which this data provides detail information is academic consulting, including the precise number of consulting contracts in which researchers are engaged.

3.2. Academic consulting

In order to fully understand the nature of our data on academic consulting, it is important to provide a brief overview on the regulation that governs the contractual arrangements that university researchers are allowed to establish with non-academic agents.

In the Spanish context, university-industry linkages are regulated by the Organic Law of Universities (LOU-2001, and specifically, Article 83). This regulation authorizes academic researchers to sign agreements with public or private organisations for the development of work of a scientific, technical or artistic nature, as well as for the development of specialisation courses or specific activities associated with training. In this sense, academics have the capacity to establish contractual arrangements with companies, and perform advisory and consulting agreements for them, provided that such contracts are established through the university – that is, through the organisational structures available at universities that have the mission to channelling knowledge and technology transfer activities.

Under this University Act, each university is autonomous in establishing procedures for authorisation of the work and monitoring consulting agreements, and to set the criteria to determine the destination of the assets and resources obtained through these agreements. In the case of the Polytechnic University of Valencia (UPV), for example, this university retains 10% of the total amount of funding from external agents in concept of overheads, while the rest of the stream of income from the contract covers the material costs involved in the development of the planned tasks and the remuneration of the academic scientist responsible for the implementation of the activities agreed in the contract. With regards to the remuneration of faculty involved in consulting activities, the income received must not exceed 1.5 times the annual salary that corresponds to the highest category of academic faculty – i.e. the category of full-time professor[1].

Considering this legal framework as our point of reference, consulting activities are identified on the basis of well-defined activities developed through contractual agreements. More specifically, the purpose of these contractual arrangements is generally an activity aimed at solving specific problems, which is not supposed to generate new scientific or technological knowledge, but can promote or facilitate technical and/or organisational innovation. In this type of contracts we find technical and professional work, including design, and technological support to industry. Consulting work also includes other type of tasks such as technical services (e.g. data analysis,

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[1] UPV's Management Regulations for Research, Technology Transfer and Continuing Education, BOUPV 43, http://www.upv.es/entidades/SG/infoweb/sg/info/U0537298.pdf.

testing) which are normally provided by universities through specialised equipment and skilled personnel available at research centres.

Drawing on the above characterisation of academic consulting, Table 1 and 2 show that academic consulting is a frequent contractual arrangement among university academics in the universities analysed in this paper. Indeed, as Table 1 shows, 49% of our sample of academic researchers has been involved at least once in academic consulting over the period 1999-2004. The proportion of scientists involved in academic consulting is generally higher than the proportion of scientists involved in R&D contracts (with the only exception of University of Valencia). It is also interesting to note that there are significant differences by scientific discipline: scientists in engineering-related fields have a much higher propensity to engage in academic consulting – above 70% of scientists in Engineering engage in academic consulting over the six-year period analysed, compared to the 40% figure for the cases of scientists which belong to the others scientific disciplines analysed (see Table 2).

[Insert Tables 1 and 2 in here]

4. METHOD AND DESCRIPTIVE STATISTICS

4.1. Method: ATT matching estimator

In order to evaluate the effect of academic consulting on scientific productivity we rely on an average treatment effect on the treated (henceforth ATT) matching estimator (Rosenbaum & Rubin, 1983). In particular, we assimilate academic consulting to a treatment conducted on a scientist that, once received, may influence his future rate of research productivity. Operationally, treatment variable D takes value 1 if an academic scientist has engaged at least in one consultancy contract and 0 otherwise.

The fundamental problem is to measure how much the scientific production of scientists is affected by carrying out consulting activities. Formally:

$$E[Y_1 - Y_0 \mid D = 1] = E[Y_1 \mid D = 1] - E[Y_0 \mid D = 1] \tag{1}$$

where $E[Y_1|D=1]$ is the average scientific productivity of those scientists conducting consulting activity while $E[Y_0|D=1]$ is the average scientific productivity we would have observed for the same scientists had they not conducted consulting activity. Evidently, the second quantity is not observable in practice and it should be approximated. Under the conditional independence assumption, the matching estimator construct a correct sample counterpart for those scientists that conducted consulting activity, had they not done it, by pairing each treated scientist with scientists of a comparison group and in this way, one is able to correctly estimate the ATT by the following equation:

$$E\big[Y \mid D = 1, X = x\big] - E\big[Y \mid D = 0, X = x\big] \tag{2}$$

Rosenbaum and Rubin (1983) show that this is equivalent to estimate the difference:

$$E\big[Y \mid D = 1, p(x) = \eta\big] - E\big[Y \mid D = 0, p(x) = \eta\big] \tag{3}$$

with $p(x) = P(D=1|X=x)$. $p(x)$ is the propensity score and is approximated via the estimate of a logistic model containing all the relevant covariates explaining the propensity to take the treatment. In our case, the *Xs* are a set of characteristics influencing the decision to engage in academic consulting.

The assumption of conditional independence turns out to be very important to consistently estimate the parameter of interest, i.e. the effect of consulting activity on the number of scientific publications of academic scientists. [2] Unfortunately, by definition, the conditional independence assumption cannot be directly tested but the availability of ample information is important to define a vector of explanatory variables that makes the assumption as plausible as possible. Theory, institutional set-up as well as previous literature are all things that can guide the correct choice of the variables used in the calculation of the propensity score and, in this way, can make more reliable the assumption of conditional independence.

The first step of our identification strategy is to estimate the following logistic model for the sample comprising full information for 2678 scientists:

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[2] Conditional independence is not the only assumption needed to consistently estimate the ATT but it is one that is more difficult to satisfy. Other conditions to be satisfied are the stable unit treatment value assumption and common support.

$$DAcademicConsulting_i = \alpha + \beta_1 PublicRD_i + \beta_2 (PublicRD_i)^2 + \beta_3 (ContractRD_i) +$$
$$+ \beta_4 (ContractRD_i)^2 + \beta_5 Experience_i + \beta_6 (Experience_i)^2 + \delta^T Z_i + \varepsilon_i \qquad (4)$$

where the dependent variable $DAcademicConsulting_i$ is a dummy variable equal to 1 if the academic scientist i engaged in academic consulting in the 1999-2002 period and its estimate constitutes the propensity score needed for the matching procedure.

As noted in the above paragraph, the choice of the model used for the calculation of the propensity score is essential in order to credibly defend the conditional independence assumption. For this reason, the choice of the independent variables to include in the model has gone through accurate scrutiny. In particular, we rely on the former literature dealing with the determinants of academic consulting at the individual level. Extant literature agrees on what the most important drivers of academic consulting are: (i) the amount of research funding from industry (Craig Boardman & Ponomariov, 2009; Landry et al., 2010); (ii) the amount of government research funding (Gulbrandsen & Smeby, 2005; Jensen et al., 2010); (iii) experience of the academic scientist (Link et al., 2007); (iv) size and orientation to applied research of the University the scientist is affiliated to (Arvanitis et al., 2008; Bekkers & Bodas Freitas, 2008; Landry, 2010) and (v) working in scientific fields particularly oriented to applied research, such as engineering and technology (Gulbrandsen & Smeby, 2005; Arvanitis et al., 2008; Bekkers & Bodas Freitas, 2008; Craig Boardman & Ponomariov, 2009; Grimpe & Fier, 2009).

On the grounds of the above results, we define the independent variables introduced in model 4 as follows. $PublicRD_i$ is the average number of research projects funded by local, national or European public bodies in the 1999-2002 period. $ContractRD_i$ is the average number of research contracts funded by private companies or public administrations in the 1999-2002 period. $Experience_i$ is a proxy for work experience and is measured as the number of *quinquenios*[3] obtained by the scientist. In order to control for the presence of a curvilinear effect in the funding of research as well as in the level of experience we also include the squared value of the last three variables: *(PublicRD_i)²*, *(ContractRD_i)²* and *(Experience_i)²*. Z_i is a vector of scientist-specific control variables; and ε_i is the error term. In particular, we control for the effects stemming from the academic position of the

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[3] In Spain, the *quinquenio* (literally a five-year period) is a form of recognition granted to academic scientists based on their experience and affects their salaries. *Quinquenios* are granted every five years, following an evaluation process. Thus, a professor who has been in a university for 20 years could possess up to 4 *quinquenios*. *Quinquenios* are generally automatic and thus can be used as a proxy for academic experience.

scientist (*DAcademicPosition$_i$*), his scientific field (*DScientificField$_i$*) and University affiliation (*DUniversity$_i$*) by including a series of specific dummies.

The second step in our identification strategy is to use the estimated propensity score (*p(x)*)[4] to match the group of scientists engaging in academic consulting with the most similar group of scientists not engaging in academic consulting which is equivalent to compute the empirical counterpart of equation 3 and provides an estimate of the ATT:

$$ATT = \frac{\sum_{i \in T} \left(NumberPub_i - \sum_{j \in M(i)} w_{ij} NumberPub_j \right)}{NT} \tag{5}$$

where *NumberPub$_i$* and *NumberPub$_j$* are the number of ISI-publications published respectively by scientists engaging in academic consulting and scientists not engaging in academic consulting in the 2003-2004 period; *T* is the set of scientists engaging in academic consulting; *NT* is the set of scientists not engaging in academic consulting; *M(i)* is the matching set for unit *i* and represents the set of control scientists we choose to match with each scientist engaging in academic consulting; w_{ij} are the weights assigned to the different units *j* which represent scientists not engaging in academic consulting. Different methods are available that choose differently *M(i)* and w_{ij}. We implement three of the most popular ones in our estimation of the ATT - i.e. nearest neighbour matching, radius matching and kernel-based matching - thus providing a robustness check of the results obtained (Caliendo & Kopeinig, 2008).[5]

In addition to the estimation of the overall effect of consulting on the productivity of academic scientists, we estimate the effect of consulting on productivity across the different scientific fields. In this case, we calculate the ATT after matching treated and controls in the same scientific field by the value of the propensity score. We do this by using the three different matching algorithms

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[4] The propensity score has been also calculated by adopting two alternative specifications where all of the covariates are pre-determined with respect to the treatment. In first alternative specification, the propensity to engage in academic consulting is defined in the 2001-2002 period while the covariates are defined in the 1999-2000 period. In the second specification, the propensity to engage in academic consulting is defined in the 2000-2002 period while the covariates are defined for the year 1999. Although the estimates are in line with those provided in the following, the smaller sample size affects the efficiency of the estimates. Thus, we decided to present the results for the specification that keeps the larger sample size. Results for the alternative specifications are available from the authors upon request.

[5] In the nearest neighbour matching, a treated unit is matched to a unit in the control group that is closest in terms of the Mahalanobis distance between the respective propensity scores. In the radius matching, the matching is done using a tolerance level on the maximum propensity score distance between nearest neighbours (caliper). In this way, not only the closest neighbour within a pre-determined distance is matched, but all the individuals in the control group within the caliper are matched together. In the Kernel-based matching, a treated unit is matched to all non-treated units in the control group, but the controls are weighted according to the Mahalanobis distance between the treated unit and each non-treated unit.

mentioned above. In this way, we are able to investigate the effect of academic consulting on the scientific productivity for scientists belonging to different scientific fields.

Traditionally the propensity score matching approach has been applied to single-treatment frameworks. Arguably, however, in the case of the effect of consulting on the productivity of academic scientists it is not only whether a scientist conducts consulting, but how much consulting he is doing that may matter. Our definition of consulting as a treatment on the academic scientist forces us to measure it as a binary variable only (doing consulting or not doing it). Providing a measure of the intensity of consulting activity at the individual scientist level allows us to investigate some of the theoretical hypotheses proposed by the existing literature, related to the existence of a curvilinear relationship between consulting and scientific productivity. The optimal solution would be to consider a continuous treatment that is equal to the number of consulting contracts obtained by each single scientist. However, the number of consulting contracts is not a continuous variable but a count variable. To cope with the count nature of our treatment variable, we rely on the approach pioneered by Imbens (2000) and Lechner (2001) who take into consideration estimation of ATT under multiple treatments. Operationally, we take into account the number of consulting contracts obtained by the academic scientists contained in our sample by grouping the number of contracts over the period 1999-2002 into predefined groups. In particular, three different intensities of treatment are taken into consideration: (i) "high" (scientists reporting more than 2 consulting contracts), (ii) "medium" (scientists reporting 1 or 2 consulting contracts) and (iii) "zero" (those reporting no consulting contracts).

4.2. Descriptive statistics of key variables

A description of the variables used in our analysis is presented in Table 3. Table 4 presents the basic statistics for the variables in the regression analysis, and their correlation coefficients. As shown in Table 4, the mean of ISI journal publications per researcher is 6. However, this variable is characterized by a highly skewed distribution and a significant overdispersion. In fact, 45% of academics did not publish during the two-year period 2003-2004, and 20% of them generated 80% of the publications. Regarding knowledge transfer activities, Table 4 shows that 36% of academics in the sample have carried out consulting activities over the period 1999-2002, compared to 24% of academics who have participated in R&D contracts over the same time period (i.e. 1999-2002).

In order to conduct a preliminary analysis of the effect of consulting activities on the scientific production of academics, we carried out a *t*-test for comparison of means for two groups of

scientists: those who conducted consulting activities over the period 1999-2002 versus those who did not. The results show that there is a statistical significant difference between the two groups of scientists. Specifically scientists who did not engage in consulting activities exhibit a statistically significant higher scientific output (Table 5).

[Insert Tables 3, 4 and 5 in here]

5. FINDINGS

The results of the econometric analysis are illustrated in Tables 6, 7, 8 and 9. Table 6 presents the estimates of the logistic model used to compute the propensity score. Table 7 reports the ATT of consulting on the scientific productivity of academic scientists. Table 8 reports the ATT of academic consulting on the scientific productivity of scientists matched according to their value of the propensity score and their scientific field. Table 9 illustrates the ATT for the intensity of consulting on the scientific productivity of academic scientists both in general and across the different scientific fields. Tables 7, 8 and 9 report the results for three different matching algorithms (nearest neighbour method, kernel-based method and radius method). In the same tables, following Caliendo and Koepeing (2008), we report a series of indicators assessing the matching quality of the procedure adopted.

Let us first consider the results shown in Table 6 where the dependent variable captures the propensity to engage in consulting activities at the scientist-level ($DAcademicConsulting_i$). $PublicRD_i$ exhibits negative coefficient, significant at the 1% confidence level meaning that academic scientists are less likely to engage in consulting activities if they obtain more research projects. This result points to the existence of a negative relationship between the ability or willingness of a scientist to obtain funding for research through competitive research projects and consulting. Moreover, the amount of research projects impact in a non-linear way the propensity to engage in consulting activity as evidenced by the positive and significant coefficient of $PublicRD_i^2$. $ContractRD_i$ exhibits a positive coefficient, significant at the 1% confidence level meaning that academic scientists are more likely to engage in consulting activities if they receive more research contracts from industry and public administrations. It is interesting to note that the amount of research contracts funded by industry and public administrations impact in a non-linear way the propensity to engage in consulting activity. Indeed, the coefficient of $ContractRD_i^2$ is negative and statistically significant at the 5% confidence level. This suggests that the contribution of an additional research contract to the probability of engaging in academic consulting decreases with

the number of contracts obtained. In the same vein, the positive and significant (at 1%) coefficient of Exp_i implies that the level of experience gained by the scientist plays a role in explaining the propensity to engage in academic consulting. As before, the squared term Exp_i^2 is negative and significant at the 1% confidence level pointing out that a non-linear relationship is likely to be present even in this case. Finally, among the controls included in the model, the scientific field and the academic position have some bearing on the scientist's propensity to engage in academic consulting. More specifically, working in applied fields such as engineering and technology increases the likelihood to carry our academic consulting. Moreover, being a lecturer has a negative effect on the propensity to engage in consulting (compared to scientists with a comparatively lower academic status).

It is worth mentioning how all of the above results are in line with those obtained by the extant literature. This is an important preliminary result reinforcing our belief that the conditional independence assumption is a reliable identifying assumption given our theoretical set-up and the results obtained by the previous literature.

[Insert Table 6 in here]

Let us now focus on the results of the ATT matching estimators where the outcome variable is always the number of ISI publications published in the 2003-2004 period ($NumberPub_i$). Table 7 reports the ATT of consulting on the scientific productivity of academic scientists following the three matching algorithms described in the previous section. In all of the three cases the effect of consulting on scientific productivity of academic scientists is negative and significant at the 1% level. In particular, engaging in consulting activity implies less ISI-publications in the following period, with the amount of neglected publications ranging, on average, between 2.23 and 3.86 (depending on the matching algorithm used). Table 8 reports the ATT of consulting on the scientific productivity of academic scientists across the different scientific fields. The ATT of academic consulting is found to be negative and strongly significant (at the 1%) in the fields of "Natural and exact sciences" and "Engineering". In the former case, engaging in consulting activity implies less ISI-publications in the following period, with the amount of neglected publications ranging, on average, between 3.07 and 4.31. In the latter, the amount of neglected publications ranges, on average, between 2.97 and 5.81. In the other scientific fields (i.e. "Medical sciences" and "Social sciences and humanities"), the ATT is not found to be significant at the usual confidence levels.

[Insert Tables 7 and 8 in here]

The result of the negative effect for the field of "Engineering and technology" is somewhat counterintuitive given that the extant literature found proximity between university and industry in applied sciences such as engineering to exert a positive effect on the productivity of the academic scientist (Calderini et al., 2009). Nevertheless, by taking into consideration the intensity of treatment we are able to better portray the relationship between consulting and scientific productivity across different scientific fields. Table 9 illustrates the results of the estimation of multiple treatment effect for overall consulting and different scientific fields. In the case of overall consulting, a negative effect on the productivity of academic scientists is found whatever the amount of consulting carried out. When the amount of consulting is high, the neglected publications are, on average, 3.07 ("high vs. zero") while if the amount of consulting is medium the number of neglected publications are, on average, lower and equal to 1.91 ("medium vs. zero"). Interestingly if the ATT for the different scientific fields is taken into consideration, a negative and statistically significant effect is found only when the level of consulting is high ("high vs. zero"). The effect in terms of neglected publications is 4.74 for scientists working in the field of "Natural and exact sciences", 0.79 for those working in the field of "Social sciences and humanities" and 3.86 for those in "Engineering and technology". When the level of consulting is moderate, no statistically significant effect is found across the different disciplines.

[Insert Table 9 in here]

Finally, it is interesting to note that we assessed the quality of all the matching procedures carried out along our work. In particular, Tables 7, 8 and 9 report the Mc Fadden's Pseudo R^2 of running the same logits with the overall sample (Pseudo R^2 before) and only with the matched sample (Pseudo R^2 after). In addition, we report whether all t-tests for the equality of means in the treated and non-treated groups cannot be rejected at the 5% significance level after matching. Finally, the mean absolute standardised bias before and after matching is reported. These tests confirm the robustness of the method used. First, the Pseudo R^2 of running the same logits with only the matched sample is always considerably lower. Second, in all cases the t-tests for the equality of means in the treated and non-treated groups cannot be rejected at the 5% significance level after matching. Finally, we find that the bias reduction after matching is always considerable.

6. CONCLUSIONS

The effect of consulting on the productivity of academic scientists has, up to now, received scant scholarly attention. Indeed, the extant literature has mainly concentrated on the impact of more formal channels of knowledge and technology transfer (such as patenting and spin-offs) on the scientific productivity of scientists, providing mixed findings that reflect different views in an ongoing open debate.

This paper provides preliminary evidence for the impact of consulting activity on the scientific productivity of academics. Taking advantage of a unique dataset containing detailed information on the activities carried out by scientists employed in five universities located in a Spanish region (i.e. Valencia Region), and using a propensity score matching estimator method, we find, on the whole, a negative impact of consulting on the productivity of academic scientists. More specifically, we find that the negative effect of conducting consulting activities can be quantified in the order of magnitude of 2 to 3 publications in a subsequent two-year period (2003-2004).

However, if we look at each of the scientific disciplines separately and the intensity of consulting activity is taken into consideration, the negative effect is found to hold only when the level of consulting activity is high: that is, when the scientists engage in 3 or more consulting activities over a 4 year period (in this case, 1999-2002). Conversely, when scientists engage moderately in consulting activities (i.e. in 1 or 2 consulting activities over the same 4 year period), no significant effect on scientific productivity is found.

Overall, one line of interpretation of these results is that, in line with the arguments raised by the scarce theoretical literature dealing with the topic (Mitchell and Rebne, 1995; Perkmann and Walsh, 2008), time spent on consulting might detract from dedication to the primary role of research, and thus negatively affect publication performance. In particular, a trade-off between consulting and research activities is likely to arise when devoting time to consulting comes at the expense of efforts oriented to research. This can be the result of what Perkmann and Walsh (2008) call 'opportunity-driven' consultancy. According to these authors, opportunity-driven consultancy is a type of consulting that provides additional sources of personal income for the scientists but it may be counterproductive for research performance if detracts a significant amount of time from research activities.

Indeed, our findings indicate that this trade-off between consulting and research performance only sets in for very high levels of engagement in consulting activities. However, when academic

scientists engage moderately in consulting activities, research performance is not affected in any significant way. This non-linear effect was consistently found in all the scientific fields investigated in our analysis. Though this is an important result, we believe it is too premature at this stage to derive implications in terms of the 'optimal' level of investment in consulting activities for scientists. As we explain below, more information is requested to run more articulated analyses accounting for other factors that might have a role in explaining the involvement in consulting activities by scientists and their publication productivity.

Overall our results pave the way for future research on the impact of consulting activities on scientists' academic productivity. Specifically we think that more accurate studies addressing the impact of consulting activities on scientists' academic productivity should take into account additional information with regard to both: a) the consultancy activity itself and b) the academic scientists.

As for the consultancy activities, it would be desirable to account for the nature or type of consulting and its actual content to analyse the extent to which consulting activities are in line with scientists' interests and the extent to which they offer insights for new research contributions. Moreover, on top of the number of consultancy activities, it would be appropriate also to account for their magnitude, such as: length, economic revenues, number of individuals involved, number of other external institutions, among other features.

With regard to scientists, a major limitation of the approach pursued in this paper is that it requires us to rely on the conditional independence assumption. Although we try to convince the reader that we controlled for all of the important covariates driving the decision to engage in consulting activity, we are not able to check whether an endogeneity problem still persists. Indeed, the selection into treatment (the decision to engage in consulting) is the outcome of a deliberate choice by the scientists. For instance, low productive individuals may be discouraged from further pursuing scientific activity and find consulting appealing in terms of personal income increase; on the contrary, more productive scientists may actually find it more rewarding to conduct research (at least from an intellectual point of view) rather than engaging in consulting. In this case, consulting would occur along with a decrease in publication activity, but would not explain the latter.

In order to address this endogeneity problem, it would be crucial to account for some additional individual characteristics (compared to those already covered in this paper), in order control for

important factors that may influence the decision to engage in consulting activity. This additional individual factors could include the following. The nature of the research activities (basic vs. applied) conducted by the scientists, since applied scientists may be more prone to get engaged in consulting activities and find in it new stimuli for their research activities. Moreover, the action of being involved in consulting activities can be explained by individuals' intention to perform a given behaviour, which in turn is influenced by individual level characteristics, including competencies, abilities, cognitive attributes, and by the environment in which scientists operate, in accordance to intention-based models (Ajzen, 1991; Krueger et al., 2000). It is reasonable to think that the latter, which accounts, among other things, for universities' polices and for the type of support that they offer to technology transfer in general, influence the individual intention to get involved in consulting activities.

Finally, although we argue in favour of a model of time allocation where time spent on consulting detracts from dedication to the primary role of research, we are unable to control for other tasks the academic scientist is likely to carry out, particularly teaching and technology transfer activities (e.g. patenting, licensing and spin-off activities). In the former case, we assume that all faculty members dedicate the same amount of time to work, face a fixed teaching load and choose the amount of time to devote to research and the amount of time to do consulting. Thus, when the amount of time dedicated to consulting activity rises, it can be only at the expense of time devoted to research. Nevertheless, the teaching load and the number of hours dedicated to work per day are not necessarily fixed and can vary through time. If this is the case, a higher amount of time dedicated to consulting can imply a fall in the teaching load, an increase of the hours dedicated to work per day or both (Thursby et al., 2007). In either case, the effect of consulting on scientific productivity is no more a direct, clear-cut one, and our estimators can be actually biased. Regarding the connection between consulting and other types of technology transfer activities, recent contributions highlight the significant complementarities arising from the different channels for knowledge transfer (Landry et al., 2010; Crespi et al., 2011): patenting activity, spin-off formation, consulting services and informal knowledge transfer. Unfortunately, given the nature of our data, we are not able to directly control for these effects and this may have some bearing on the consistency of our estimators.

Future work should try to address all the points mentioned above to extend our results. In spite of these limitations, we believe that the insights gained from our study will serve as a guide and

foundation for future work aimed at investigating the effect of academic consulting on scientific productivity.

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Table 1. Proportion of active researchers who engage in consultancy and R&D contracts over the period 1999-2004, by university (%):

	Consultancy	R&D Contracts	N. obs.
UA	43	29	349
UJI	44	33	189
UMH	51	16	249
UPV	68	27	881
UV	36	41	1010
Total	49	32	2678

Table 2. Proportion of active researchers who engage in consultancy and R&D contracts over the period 1999-2004, by field of science (%):

Scientific Field	Consultancy	R&D Contracts	N. obs.
Natural & Exact Sc.	42.6	32.0	1040
Engineering	72.2	32.7	593
Medical Sc	41.3	30.6	196
Social Sc. & Humanities	42.5	32.4	817
Total	*49.1*	*32.9*	*2646**

* There are 32 missing values regarding scientific field.

Table 3: Description of the variables used in the logistic regression

Variable	Description and scale
NumberPub	Scientific Production. Nº of articles published by each researcher in journals ISI 2003-2004 period
DAcademicConsulting	Dummy variable equal to 1 if the academic scientist *i* engaged in academic consulting in the 1999-2002 period
ContractRD	Average number of research contracts funded by private companies or public administrations in the 1999-2002 period
PublicRD	Average number of research projects funded by local. national or European public bodies in the 1999-2002 period
Experience	Number of "quinquenios" obtained by the professor during their life work: 1"quinquenio" is equal to 5 years of work experience
DAcademicPosition	Dummy Variable of 1-3. Academic position of the scientist : 1.Other; 2. Lecturer and 3. Professor
DScientificField	Dummy Variable of 1-4. Researcher's scientific field to which the researcher belongs: 1. Natural and exact sciences; 2. Engineering; 3. Medical Science and 4. Social Science and humanities
Duniversity	Dummy variable of 1-5. University to which the researcher belongs: 1.UA; 2.UJI; 3.UMH; 4.UPV; 5.UV

Table 4. Descriptive statistics and Spearman's correlation coefficients

	Mean	S.D	Min	Max	NumberPub	Dacademic Consulting	ContractRD	PublicRD	Experience	Professor	Lecturer	Others	Natural & Exact Sc.	Engineering	Medical Sc	Social Sc. & Humanities
NumberPub	5.90	11.8	0	99	1											
Dacademic Consulting	0.36	0.5	0	1	-0.05	1										
ContractRD	0.14	0.5	0	17.5	0.05	0.14	1									
PublicRD	0.28	0.5	0	12.5	0.25	0.01	0.52	1								
Experience	3.28	1.8	0	8	0.04	0.06	0.11	0.21	1							
Professor	0.26	0.4	0	1	0.22	0.10	0.13	0.28	0.53	1						
Lecturer	0.49	0.5	0	1	-0.06	-0.14	-0.02	-0.01	-0.11	-0.58	1					
Others	0.25	0.4	0	1	-0.15	0.06	-0.11	-0.27	-0.46	-0.34	-0.57	1				
Natural & Exact Sciences	0.39	0.5	0	1	0.24	-0.08	-0.01	0.10	0.05	-0.01	0.07	-0.07	1			
Engineering	0.22	0.4	0	1	0.03	0.23	0.03	-0.08	-0.15	0.00	-0.19	0.22	-0.43	1		
Medical Sciences	0.07	0.3	0	1	0.03	-0.06	0.00	0.04	0.07	0.01	0.05	-0.06	-0.23	-0.15	1	
Social Sc. & Humanities	0.31	0.5	0	1	-0.29	-0.09	-0.02	-0.05	0.04	0.00	0.08	-0.09	-0.54	-0.36	-0.19	1

Beyond 0.04 the correlation coefficients are significant at standard levels (5%).

Table 5. Comparison of means of scientific productivity in the different group of academic scientists

Group	Scientific productivity T- test		
	Nº Obs	Mean	T
1. Scientist engaged in consulting	1702	6.4	2.898**
2. Scientist not engaged in consulting	976	5.0	

** p<0.05

Table 6: Logit estimation of the propensity score

		$DAcademicConsulting_i$
	Constant	-1.606***
		(0.225)
β_1	$PublicRD_i$	-1.069***
		(0.257)
β_2	$PublicRD_i^2$	0.458***
		(0.139)
β_3	$ContractRD_i$	1.646***
		(0.227)
β_4	$ContractRD_i^2$	-0.192**
		(0.084)
β_5	Exp_i	0.431***
		(0.123)
β_6	Exp_i^2	-0.034**
		(0.017)
	Academic position dummies (reference category: Other)	
	Lecturer	-0.382***
		(0.144)
	Professor	-0.168
		(0.181)
	Scientific field dummies (reference category: Natural and exact sciences)	
	Medical sciences	-0.025
		(0.192)
	Social sciences and humanities	0.014
		(0.115)
	Engineering and technology	0.685***
		(0.132)
	University dummies	yes
	Log-likelihood	-1414.114
	χ^2	342.370
	Mc Fadden's R^2	0.108
	# of observations	2428

* $p<0.10$.. ** $p<0.05$.. *** $p<0.01$.

Table 7: Estimation of the average effect of consulting on the scientific productivity of academic scientists engaging in consulting activity

	Outcome variable: *NumberPub$_i$*		
Matching_Algorithm	**Nearest Neighbor**	**Radius**	**Kernel**[+]
ATT: DAcademicConsulting	-3.86***	-2.23***	-2.39***
# of treated observations	869	872	869
# of untreated observations	869	1556	1556
Quality of matching			
Pseudo R^2 before	0.11	0.11	0.11
Pseudo R^2 after	0.01	0	0
Mean absolute standardised bias before matching	19.49	19.49	19.49
Mean absolute standardised bias before matching	3.66	2.23	1.23
t-tests for equality of means in the treated and non-treated groups	yes	yes	yes

** p<0.05.. *** p<0.01.
[+]The calculation of the standard errors is done using bootstrap with 500 replications (see Lechner.. 2002)

Table 8: Treatment effects estimations for different scientific fields

Matching_Algorithm	Natural and exact sciences			Medical sciences			Social sciences and humanities			Engineering and technology		
	Nearest Neighbour	Radius	Kernel[+]	Nearest Neighbour	Radius	Kernel[+]	Nearest Neighbour	Radius	Kernel[+]	Nearest Neighbour	Radius	Kernel[+]
ATT: DAcademicConsulting	-4.31**	-3.22***	-3.07***	-2.18	0.21	-0.36	-0.17	-0.32	-0.37	-5.81**	-2.98**	-2.97**
# of treated observations	304	303	300	50	50	50	221	221	221	290	290	290
# of untreated observations	304	659	659	50	135	135	221	544	544	290	218	218
Quality of matching												
Pseudo R^2 before	0.1	0.1	0.1	0.11	0.11	0.11	0.1	0.1	0.1	0.07	0.07	0.07
Pseudo R^2 after	0.02	0.02	0.01	0.11	0.04	0.03	0.02	0.04	0.04	0.01	0.02	0.01
Mean absolute standardised bias before matching	18.28	18.27	18.27	29.28	29.28	29.28	17.25	17.25	17.25	19.45	19.45	19.45
Mean absolute standardised bias before matching	6.77	6.59	5.27	16.77	11.95	9.82	8.33	12.43	13.29	3	5.12	3.65
t-tests for equality of means in the treated and non-treated groups	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

** p<0.05.. *** p<0.01.
[+]The calculation of the standard errors is done using bootstrap with 500 replications (see Lechner.. 2002)

Table 9: Estimation of multiple treatment effect for overall consulting and different scientific fields

	Overall			Natural and exact sciences			Social sciences and humanities			Engineering and technology		
	High vs zero	High vs medium	Medium vs zero	High vs zero	High vs medium	Medium vs zero	High vs zero	High vs medium	Medium vs zero	High vs zero	High vs medium	Medium vs zero
ATT: DAcademicConsulting	-3.07***	-0.18	-1.91***	-4.74***	-0.24	-2.3	-0.79***	0.11	-0.24	-3.86**	-0.81	-2.44
# of treated observations	397	397	472	125	130	176	81	80	137	166	166	122
# of untreated observations	1556	472	1556	659	177	659	544	137	544	218	124	218
Quality of matching												
Pseudo R^2 before	0.19	0.08	14.03	0.18	0.07	0.05	0.21	0.12	0.06	0.12	0.08	0.05
Pseudo R^2 after	0	0	1.81	0.02	0.02	0.02	0.07	0.05	0.05	0.02	0.03	0.03
Mean absolute standardised bias before matching	29.37	16.44	0.05	26.68	16.08	13.51	28.92	20.9	11.57	26.28	21.17	14.14
Mean absolute standardised bias before matching	1.95	1.75	0	8.9	6.89	8.16	15.81	13.06	12.49	6.61	8.71	7.3
t-tests for equality of means in the treated and non-treated groups	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

** p<0.05.. *** p<0.01.

Results of kernel matching are reported. The calculation of the standard errors is done using bootstrap with 500 replications (see Lechner.. 2002).

Three different intensities of treatment are taken into consideration: (i) "high" (scientists reporting more than 2 consulting contracts).. (ii) "medium" (scientists reporting 1 or 2 consulting contracts) and (iii) "zero" (those reporting no consulting contracts).

Results for "Medical sciences" are not reported due to the low number of observations available.