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Citation Impact of Public and Private Funding on Nanotechnology-Related Publications

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Abstract

This paper analyzes the effects of public and private funding on the subsequent scientific output of academic research in nanotechnology. We investigate whether public grants increase the citation of publications, as well as whether private funding is complementary in enhancing citation impact. Using panel data, we compare autoregression models, binary case and continuous treatment analysis to find evidence that funding can positively affect the citation rate of scientific publications. The results show that the influence of public grants on the number of citations follows almost an inverted U shape curve, which has a positive impact proportional to the amount of public funding received. In contrast, industry funding does not exhibit robust effectiveness on citations. The estimates suggest that private research funding from industry can be detrimental to publication impact.

Keywords: Research funding, Private funding, Scientific papers, Citations, Nanotechnology

1 Introduction

In the past decades, the government has supported nanotechnology research through greater amounts of public grants awarded to academic research in this emerging technology. Various scholars (Canton, 2001, 2007; Knol, 2004; Lorenzoni et al., 2009; Schummer and Baird, 2006; Vokhidov and Dobrovol'skii, 2010) who have studied the anticipated economic value of this field have forecasted that nanotechnology applications will undoubtedly stimulate economic growth. This has led to a rapid increase in nanotechnology funding and subsequent research growth to meet this challenge; a phenomenon exemplified by a tremendous augmentation of the number of

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nanotechnology publications at the international level over recent years (Hullmann, 2006; Roco, 2011; Ye et al. 2012; Youtie, 2008).

Although federal funding is responsible for a considerable portion of university funding, this new technology also attracts a substantial amount of private funding, despite the fact that nanotechnology is still inherently closer to basic research (Knol, 2004; Lorenzoni et al., 2009; Payne and Siow, 2003; Schummer and Baird, 2006). In general, although basic research is significant for the development of new technologies (Rubini, 2010), it is less likely to attract private funding and requires sufficient government funding because it is difficult to forecast or even measure its economic value. Dasgupta and David (1994) rightfully showed that the outcomes of basic research are highly uncertain and economic payoffs are not properly observed in the short term. In this respect, private companies mainly follow short-term objectives rather than blue-sky research. Yet according to Gulbrandsen and Smeby (2005), private funding might have a role in defining research topics, since researchers with more industry funding collaborate more with other scientists and their research is described as more applied. Identifying the distinctive impact of public and private funding in this research will thus contribute to our understanding of the efficiency of funding allocation. This is particularly important in light of the recent investments in nanotechnology research.

Previous studies chiefly focused on government funding in academic research, generally showing that federal funding has a small positive impact on publication quality (Jacob and Lefgren, 2011; Payne and Siow, 2003). It is not yet clear from the literature, which still lacks sufficient studies on this issue (especially regarding scientific quality), whether research funding from private sources has an impact, either positive or negative, on scientific productivity and quality. The lack of studies is primarily due to confidentiality issues respecting this type of company-related data, which often preclude scholars from gaining access to such private investments. Accordingly, most prior studies suffer from a lack of information on private funding, particularly at the level of the individual researcher. Our access to privileged information about private contracts for Quebec academic researchers gives us the opportunity to remedy this lack of evidence.

As one of the most active Canadian provinces in terms of nanotechnology investment, science, research and development since 2001, Quebec has initiated considerable financial support. The creation of NanoQuébec in 2001 is one example of this public support (NanoQuebec, 2010). Our paper thus complements the studies that find a positive impact of public funds on scientific productivity by focusing on the other important source of funding – industry investment in a high technology field that has been growing over the last few decades. We therefore aim to measure the influence of funding on academic research and to compare the impact of two funding sources, public and private. Following the work of Beaudry and Allaoui (2012) on nanotechnology publications, in this study we focus on the quality of scientists' publications as a measure of a scientist's impact rather than on scientific productivity.

Understanding the impact of different sources of funding is critical and can result in the efficient allocation of these investments singly or in combination, which then generates higher quality research outputs. This paper offers important contributions to the literature to enhance understanding of the impact of public and private research funding on the quality of publications in an emerging field. For instance, our results show that although public funding has considerable impact on the quality of publications generated by Quebec nanotechnology scientists, private funding has a strong negative impact, even when controlling for these academics' patenting activities.

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework, based on the literature that has inspired our research hypotheses. Section 3 describes the data, the variables and the methodology employed. Finally, regression results are analyzed in Section 4 and concluding remarks are presented in Section 5.

2 Conceptual framework

In recent years, many countries have increased their investment in nanotechnology research in universities in order to encourage future innovations (Bhattacharya, 2007; Canton, 2001; Davies, 2007; Hullmann, 2006; Knol, 2004; NSF, 2001). The findings of Seear et al. (2009) illustrate that government and corporate investment are the main sources of global nanotechnology research funding. According to Roco (2011), worldwide investment in nanotechnology R&D from both the public and the private sectors was \$15 billion in 2008, resulting from a 35% average annual growth between

2000 and 2008. Providing the complex infrastructure and instruments to develop nanotechnology research requires access to sufficiently large amounts of investment in order to foster knowledge development in this multidisciplinary field. After examining the US government science and technology programs under the National Nanotechnology Initiative (NNI), Jung (2014) suggested that their programs and funding increase the efficiency of university research.

Policymakers requiring evidence of performance and benefits of funded research increasingly demand a demonstrated relationship between funding and research performance, as funding sources are scarce and need to be effectively employed (Kuhlmann, 2003; Shapira and Furukawa, 2003).

Most prior studies examined the frequency of publications as a performance indicator, while only a few focused on research quality. The publication rate of research outputs has been more commonly investigated. For example, Adams and Griliches (1998) found that, at the aggregate level (group of universities), the relationship between scientific output (measured by both the number of publications and citations) and research funding exhibits a constant return of the production process, while at the individual university level, the relationship shows diminishing returns. In addition, the authors made a distinction between federal research funding and non-federal funding, which could be construed as closer to private funding. They found the elasticity of non-federal funding to be systematically lower than that of federal funding, implying that public research funds have a more important impact. In another study, Boyack and Börner (2003) suggested that there is little correlation between government funding and citation rates of research publications in the behavioural and social sciences. According to a study by Payne and Siow (2003) on 74 research universities, government funding has a positive influence on university research outputs, although the effect on the number of citations is small and imprecise. In the same vein, Jacob and Lefgren (2011) also suggested a relatively modest effect of National Institutes of Health (NIH) grants on the number of citations obtained by publications resulting from NIH grants. While Shapira and Wang (2010) found mixed impacts on citations, Lewison and Dawson (1998) showed that the number of funding sources matters in publishing articles in higher impact journals. Chen et al. (2013) also found a significant increase in citations with an increase in public funding. Using a dataset of scientists active in the natural sciences and engineering, Ebadi and Schiffauerova (2016) confirmed that a higher level of funding boosts researchers' scientific performance.

The receipt of public grants exerts leverage on the capacity to raise further research funds. The findings of Jacob and Lefgren (2011) show that in the US, receiving NIH funding influences the capacity to raise funding from other sources such as the National Science Foundation (NSF) and private sources (i.e. from industry). A study of US universities revealed that receiving federal funding from NSF and NIH can be a sign of recipient quality and increases the chance of receiving non-federal funding (Blume-Kohout et al., 2009). These non-federal organizations assume that federal funding reflects higher quality, which prompts them to allocate additional funding. Researchers unsuccessful in obtaining public funding must however find other sources in the private sector. There thus seems to be a substitute/complement ambiguity related to public and private funding. Muscio et al. (2013) showed not only that public funding complements private funding to universities, but also that the ability to produce high-quality research is necessary for universities to receive industry contracts. They argued that public funding strategically plays an important stimulus role in raising funding from industry contracts.

Previous studies have used different quantitative and qualitative methods to measure how funding influences academic research. Wallin (2005) showed that bibliometric indicators require precise knowledge and should accordingly be used correctly to obtain appropriate results. Some studies however raised a general concern in using citations: the number of citations may be due to the growth or development of a specific field, or researchers may discover a flaw in a paper and endeavour to correct it in a new publication (Kostoff, 1998; MacRoberts and MacRoberts, 1996; Wallin, 2005). Citation analyses are frequently used to identify valuable research and to assist grant-awarding bodies in the efficient allocation of investment (Agasisti et al., 2012; Laudel, 2005; Rigby, 2011). Bloch et al. (2014), who considered bibliometric analysis to study the impact of grants on research, found that this approach can provide useful results. A study by Gök et al. (2015) on the impact of research funding on publications in six small European countries showed that funding is tied to the number of citations rather than to the first citation. They found that the structure of funding also matters.

Other works emphasized the importance of collaboration and social networks on the impact of funding on citation of papers. Adams et al. (2005), for example, noted that public funding affects the size of scientific teams, which in return leads to more citations. Scientists with prestigious awards and a large stock of federal funding do in fact collaborate in larger teams, and this collaboration generally provides better opportunities for their work to be cited more frequently. A study by Maas et al. (2016) reports that funding in health fields is positively associated with higher quality.

In light of the evidence presented in the literature, we propose the following hypothesis respecting the impact of public grants on the number of citations obtained by nanotechnology-related publications:

Hypothesis 1: *Nanotechnology scientists who raise greater amounts of public funding also obtain more citations for their publications.*

The current debate exposes very different views on how the integration of university research with industry can also influence research outputs. Some studies indicate that increased links with industry have a positive impact on scientific outputs (Abramo et al., 2009; Baba et al., 2009; Banal-Estanbol et al., 2011; Guan & Wang, 2010; Landry et al., 1996; Siegel et al., 2003), while others argue that they have a negative impact (Argyres and Liebskind, 1998; Owen-Smith and Powell, 2001; Siegel et al., 2003; Ambos et al., 2008). For example, Lexchin (2005) showed that industry funding hampers scientific progress and may result in halting research in mid-flow. Banal-Estanol et al. (2008) suggested that an average level of industry collaboration yields higher quality research outputs, although the number of publications diminishes with higher levels of private funding and industry involvement. Blumenthal et al. (1996) and Gulbrandsen and Smeby (2005) noted that industry funding positively contributes to academic productivity. Bruno and Orsenigo (2003) highlighted the importance of university productivity in attracting industrial funds, as scientifically productive universities are more likely to receive high levels of funding. These previous studies however aimed at discovering the impact of collaboration between universities and industry rather than at directly analyzing the effects of funding from industry.

Empirical evidence remains mixed as to the comparative efficiency of government funding and of industry support. Diamond (2006) counted the number of citations a paper received over a seven-year period, observing that privately funded research is more successful in this respect. Consequently, industry grants are positively correlated with higher quality research. Conversely, when Boumahdi et al. (2003) weighted publications using the impact factor of their journals, which signals the quality of research, they found that the correlation between private funding and publication performance corrected for this impact is negative. The authors suggested that organizations receiving private funding might seek research that is closer to application, while the research appearing in the higher impact journals is more likely to be fundamental. In contrast, when Behrens and Gray (2001) compared industry-sponsored projects with government-supported university projects, they found no difference in the research quality of the resulting publications.

Despite the mixed evidence presented above, our second hypothesis proposes that private funds resulting in industry links with academic research have a positive impact on the number of citations obtained by nanotechnology-related publications:

Hypothesis 2: *Nanotechnology scientists who receive greater amounts of private funding also obtain more citations for their publications.*

3 Methodology

3.1 Data and Variables

The data used in this paper derives from a unique dataset of Quebec scientists that relies on a combination of several sources: Elsevier's Scopus provides information on publications and authors; public and private funding information is available via the Système d'Information sur la Recherche Universitaire (SIRU) of the Quebec Ministry of Education, Leisure and Sports; and the United States Patent and Trademark Office (USPTO), the federal agency for granting US patents and registering trademarks, provides information on inventors and patents[2] (name, affiliation, city, application date, grant date, assignees, etc.). We prefer to use the US database because Canadian inventors largely tend to register their patents with the USPTO (Beaudry and Schiffauerova, 2011). We chose Scopus from among the most frequently used scientific databases (Science Direct, Scopus, Web of Science, Microsoft Academic Search, Scirus, Google Scholar, etc.) because it covers a wide diversity of fields and journals and, more importantly, generally matches individuals with their affiliations, thereby greatly facilitating the disambiguation of similarly named scientists. Given the multidisciplinary nature of nanotechnology, a wide range of disciplines is crucial for the purpose of this study.

SIRU contains information on both government and industry funding awarded to all university scientists in Quebec over a period of 20 years (1985–2005).[3] The data comes directly from the university accounts for each project and provides exact data on a yearly basis.[4]

We used the nanotechnology keyword queries of Porter et al. (2008) to extract the relevant nanotechnology papers and patents, from which we in turn extracted the names of individuals that we then matched to the other databases to build the final dataset. Matching was not trivial as our approach involved matching data using scientists' names. This process is likely to result in possible errors in uniquely identifying scientists having similar names (synonymy) or assigning different IDs to the same scientist whose name is spelt differently in various databases (homonymy). To circumvent these common problems, we utilized a variety of other information about scientists to define a unique ID for each academic researcher and thus minimize the incidence of wrong matches. The main information was provided by the affiliation of scientists in both Scopus and SIRU, as well as the address of academic inventors in the USPTO database. However, a significant amount of manual work and careful examination was necessary to clean the data and assign a unique ID number.

To validate the hypotheses set out in the previous section, we needed to integrate these publications, patents and funding databases into one dataset using the unique ID for each scientist. We then condensed these databases to obtain data on a yearly basis (panel data) containing the number of publication and patents, the number of citations, and the amount of grants and contracts per scientist and per year.[5]

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[2] Patents are used as control variables and will be described further in this section.

[3] The data are available for this period and not for subsequent years.

[4] Any funds that do not transit via the university system are not available. However, given the size of the grants awarded and the necessity for expensive infrastructure, we estimate the hidden funds to be minimal.

[5] We finally restricted our resulting sample data to 1996–2005, after having calculated the lagged variables on three-year and five-year averages. The reason for concentrating on this subset is twofold: first according to the growth of nanotechnology research outputs, scientists had only started being involved in this emerging area just before 1996, and the data is rather scarce prior to that period; hence this timeframe seems too early for nanotechnology. Second, there has been a considerable change for the better in the quality of

The literature generally indicates that higher-quality research receives more citations (Kostoff, 1998; Lin et al., 2007; MacRoberts and MacRoberts, 1996; Wallin, 2005; Weingart, 2005). However, there is a positive correlation between the importance of a paper and the degree to which a paper is cited in later research publications. According to Kostoff (1998), citations provide links to the historical context of specific contributions to papers and highlight a wide interest in those contributions. We define *nbArtCit3* as the number of citations the articles published received within three years[6] of publication. During the course of this research, we tried different dependent variables. The average number of citations per paper did not provide robust results, nor did the h-index calculated on a yearly basis (it is important to note here that we used panel data for our analyses). In fact, the h-index[7] is somewhat inappropriate because it evaluates the impact of an individual over the course of a career, while we are interested here in whether better funding enhances paper citations on a yearly basis.

We assessed the influence of funding on publication quality based on average amounts of public grants (*AvgGrant3*) and private contracts (*AvgContract3*) over the past three years. Yearly measures proved too volatile to provide robust results, while longer periods (five years for instance) reduced the sample size because of unreliable data prior to 1996 and were very rarely significant. In addition to these two variables of interest, our models include a number of controls, which are described in the following paragraphs.

Industry contracting often fosters patenting activities and may contribute to increasing university patents because firms are generally associated with applied knowledge and focus on short-term objectives. Patenting can however be the result of both government and industry funding. To our knowledge, few studies in the literature address the effect of academic patenting on research quality, although more debates exist on publishing-patenting trade-offs. Azoulay et al. (2009), for instance, found a positive effect on the rate of publications, but a weak effect on publication quality. A study by Breschi et al. (2008), based on a sample of 592 Italian academic inventors, showed that academic inventors publish more and better quality papers compared to their non-patenting colleagues. We

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Scopus and SIRU after 1996. There was a 1996 barrier for the Scopus data at the time of this research. As of 1 November 2014, they began to launch a program to add cited references going back to 1970 (http://blog.scopus.com/)

[6] We have calculated citations after three, five and seven years but present the three-year citations in this paper as they provided the most consistently significant results in the regressions.

[7] The h-index is an indicator based on the set of the most cited papers.

therefore sought to examine the reinforcing or limiting effect of patenting activity on nanotechnology publication citations. We thus included the number of patents to which researchers have contributed in the past years (*nbPatent*) in the models in order to examine the influence of innovative activities on the research quality. In addition, to take researchers' past publications into account from a publication track record, we included the average number of papers published over the past years (*AvgnbArticle*), lagged one year.

In the theoretical framework, we alluded to the fact that research is usually performed within collaborative teams rather than alone. Many scholars have studied the impact of collaboration on research productivity (Eblen et al., 2012; Lee and Bozeman, 2005; Sala et al., 2011; Wang and Guan, 2010). Studies have generally found that increasing levels of collaboration within scientific networks have a positive impact on scientific productivity (Frenken et al., 2005; Glänzel and Schubert, 2005; Rigby and Edler, 2005). Ebadi and Schiffauerova (2016) suggested that scientists benefit from collaboration as it increases their productivity and the quality of their scientific outputs.

Balconi et al. (2004) specifically suggested that working in collaboration with other scientists helps academic scientists gain a higher citation rate. Within networks, co-authorship enhances research performance (Baba et al., 2009; Balconi et al., 2004; Breschi et al., 2006; Ni et al. 2011; Singh, 2007; Wang and Guan, 2010; Youtie et al., 2013). Social network analysis provides sophisticated tools to measure the importance of various individuals in the co-publication network. The resulting network characteristics can thus be used as controls for collaborative work. Better-positioned researchers in the co-publication network are more likely to attract citations due to their enhanced reputation. In order to investigate a scientist's position in scientific networks, Pajek[8] software was used to characterize the networks of co-authors.

More precisely, we calculated two network indicators: the betweenness centrality (*BtwCent*) and individual cliquishness (*Cliqness*) of researchers in three-year moving intervals within co-authorship networks. Betweenness centrality measures the importance of a researcher as an intermediary position in the network. For one specific researcher, this attribute is measured by the sum of the shortest paths between two researchers that include this researcher over the total number of possible shortest paths between the two (Brandes, 2001; West, 2001). Individual cliquishness refers to the clustering coefficient of a researcher in the network, defining the probability of a connection between two researchers if both are connected to a mutual third collaborator (Barabasi, 2002). The clustering coefficient, used as a measure of cliquishness, is high for researchers who co-author articles in a highly interconnected subfield, and low for an individual researcher who collaborates widely with other researchers who tend not to publish together (Pike, 2010).

In this study, these network indicators are calculated in a co-publication network that we mapped showing the collaborative links of co-authorship between scientists as edges, and scientists as nodes in the network. The time windows we considered to construct the networks are three and five years. The three-year sub-networks gave us more consistent results, and we then chose three-year intervals with a two-year lag to build the network metrics (betweenness centrality and cliquishness) aimed at identifying the importance of a researcher in the network. We created three-year co-authorship sub-networks for all the three-year moving intervals using the social network analysis software Pajek, which is considered to be very suitable for the analysis of large networks (Batagelj and Mrvar, 1998).

Finally, we added year dummy variables to account for residual time-related effects. Table A.1 in Appendix A presents the variables and their definitions. Tables A.2 and A.3 show the standard descriptive statistics and correlation table.

3.2 Model Specification

Our model relies upon the assumption that the number of citations of scientific articles published by academic researchers depends on the average amount of research funding that a researcher receives from government and industry sources. Since our data is built as a panel (both cross-section and time series), we first use an autoregressive model in which a value from a time series is regressed on previous values from the same time series (regressed against its own lagged values). In this modeling, since the previous time period becomes a predictor, we forecast the response variable using a linear combination

[8] The social network analysis software Pajek allows the analysis of large networks.

of past values of the variable. This stochastic process operates under the assumption that the past values have an effect on current values (Arellano and Bond, 1991; Arellano and Bover, 1995). To estimate the impact of research funding on the number of citations, the system of dynamic panel data estimations suggested by Arellano-Bover/Blundell-Bond (system estimator command *xtdpdsys* in Stata 14) was used, as some of the regressors are not strictly exogenous. Higher quality outputs receive more funding, which in turn may contribute to generating more publications, which then receive more citations and facilitate raising further research funding. Demonstrating that federal funding is allocated to higher quality researchers, Blume-Kohout et al. (2009) found that this signal also affects the non-federal funding raised. Private companies use the attribution of government funding as a sign of researchers' quality to identify higher quality scientists with whom to collaborate. Our funding variable (*AvgGrant3*) is therefore likely to be endogenous due to its potential correlation with other explanatory variables. Furthermore, funding is assigned to higher quality and more highly cited researchers, who are more likely to receive more citations for their later publications. Thus, these autoregressive models use the lagged values of the dependent variable as instruments to produce efficient estimates.

Arellano and Bond (1991) developed a generalized method of moments (GMM) estimator, which yields consistent parameter estimators. This approach is designed for situations where there are a large number of cross sections and a small number of time periods (Blundell and Bond, 1998), as is the case with our data. In this paper, we use both the robust and the system GMM approaches to estimate the models and the lagged level of our dependent variable; i.e. the number of citations has been included as an additional explanatory variable allowing for serial correlation of unknown form.

$$\ln(nbArtCit3_{it}) = f\begin{pmatrix} \ln(nbArtCit3_{it-lag}), \ln\left(AvgGrant3_{it-1}\right) \\ \ln(AvgContract3_{it-1}), (\ln(10^4 \times BtwCent_{it-2})) \\ (\ln(10^3 \times Cliqness_{it-2})), nbPatent_{it-1} \\ nbArticle_{it-1} \end{pmatrix} \quad (1)$$

Second, we used non-parametric methods and conducted complementary analyses using propensity score matching methods to compare the effect of raising grant/contract funding on research outcome by comparing treated researchers, those who received funding, with their matched twins. This matching technique identifies an untreated set of researchers so that we can create a counterfactual that yields an unbiased average treatment effect on the treated researchers (ATT).[9] A number of different matching methods[10] using propensity scores have been used in the past. We used different matching methods and found the best balance using Mahalanobis matching, incorporating the caliper method to improve the quality of our matching. In the Mahalanobis method, the distance between the treated and control subjects is calculated and they are then matched based on the smallest distance. Since propensity score matching does not specifically account for panel data, we used the mean of variables and implemented the method using the psmatch2 command in Stata.

Assessing the matching quality is an important step when using matching techniques. We had to check the success of matching to determine whether this procedure was able to balance the distribution of the variables in both the treated and the non-treated groups. A simple *t*-test was used to investigate whether the mean value of variables is the same in the treatment and in the control groups. The covariates should be balanced after matching; no significant differences should be found if both samples are well matched.

In many public policies, a different "quantity" or "amount" of treatment may yield different outcomes, which in our case translates into "different funding amounts raised by individual scientists may provide different responses to the funding policy" (Royston and Altman, 1994). Thus, to better evaluate policy interventions, binary treatment status is not sufficient; the level of exposure needs to be taken into account (Hirano and Imbens, 2004).

In addition to propensity score matching, we further exploited our data using continuous treatment models. While the propensity score analysis focuses on the binary treatment, an extension of this method consists in setting a continuous rather than a binary treatment (treated vs. non-treated).[11] In such settings, the marginal causal effect can be reported from the estimated dose response function. In estimating a dose response function, we

[9] For more examples on this technique, see Kölling (2015); Leuven and Sianesi (2015); Palmer and Alda (2016); Vildo and Masso (2009).

[10] Stratified matching, Nearest neighbour matching, N:N matching, Radius matching, Kernel matching, Mahalanobis metric matching and Caliper matching.

modeled the outcome as a function of the treatment and of observed covariates using regression approaches. The dose response function is approximated by linear regression or polynomial regressions.

In this paper, we use an econometric model for a dose response function, using the *ctreatreg* command in Stata, a program proposed by Cerulli (2015) for the practical estimation of dose response functions. This model estimates the causal effect of the treatment on an outcome within the sample observed and assumes that treated and untreated units probably respond differently to the level of treatment and to specific observable confounders. The *ctreatreg* command also has the advantage of addressing non-normal distributions and is well suited when many individuals have zero as the level of treatment.

4 Regression Results

Our analyses considered numerous factors and lag structures for variables to achieve the most consistently significant results. Furthermore, we used various models with these different lag structures for our dependent and independent variables. The results of the three types of models described above are presented in the next three sections.

4.1 Results of the autoregressive model

Table 1 presents the basic estimates for the effect of public and private funding on the number of three-year citations. These are the results of system estimator command *xtdpdsys*. For all models, we present the robust regressions and the GMM using hierarchical modeling for a three-, two- and one-lag autoregressive structure (see Table A.4 and Table A.5 in the Appendix).

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[11] For more examples on this method see Cerulli (2015), Cerulli and Poti (2014), Peluffo (2016), and Siegel (2014).

Table 1 Regression results of autoregressive model – *xtpdsys*

ln(nbArtCit3$_t$)	GMM-lag3	GMM-lag3	GMM-lag2	GMM-lag2	GMM-lag1	GMM-lag1
	(1)	(2)	(3)	(4)	(5)	(6)
ln(nbArtCit3$_{t-1}$)	0.1910***	0.4568***	0.0886***	0.1568***	0.0870***	0.0971 ***
	(0.0155)	(0.0221)	(0.0116)	(0.0135)	(0.0089)	(0.0098)
ln(nbArtCit3$_{t-2}$)	0.1492***	0.3669***	0.0396***	0.0788***		
	(0.0157)	(0.0205)	(0.0113)	(0.0120)		
ln(nbArtCit3$_{t-3}$)	0.1562***	0.3483***				
	(0.0149)	(0.0191)				
ln(*AvgGrant3$_{t-1}$*)	0.0046	0.0102***	0.0057**	0.0115***	0.0100***	0.0114 ***
	(0.0029)	(0.0032)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
ln(*AvgContract3$_{t-1}$*)	0.0023	0.0500***	0.0028	0.0432***	0.0059*	0.0397 **
	(0.0035)	(0.0174)	(0.0034)	(0.0160)	(0.0034)	(0.0157)
[ln(*AvgContract$_{t-1}$*)]^2		-0.0043**		-0.0036**		-0.0032 **
		(0.0017)		(0.0016)		(0.0015)
nbPatent$_{t-1}$	0.0341***	0.1238***	0.0374***	0.1346***	0.0476***	0.1330 ***
	(0.0112)	(0.0257)	(0.0108)	(0.0236)	(0.0109)	(0.0232)
[*nbPatent$_{t-1}$*]^2		-0.0021***		-0.0020***		-0.0019 ***
		(0.0007)		(0.0006)		(0.0006)
ln($10^4\times$*BtwCent$_{t-2}$*)	0.0547**	0.0912***	0.0451*	0.0552*	0.0690***	0.0459 *
	(0.0239)	(0.0310)	(0.0232)	(0.0284)	(0.0233)	(0.0279)
ln($10^3\times$*Cliqness$_{t-2}$*)	-0.0051	0.1462*	0.0026	0.0839	0.0149***	0.0462
	(0.0039)	(0.0778)	(0.0037)	(0.0714)	(0.0037)	(0.0699)
[ln($10^3\times$*Cliqness$_{t-2}$*)]^2		-0.0198*		-0.0100		-0.0044
		(0.0113)		(0.0103)		(0.0101)
AvgnbArticle$_{t-1}$	-0.7532***	-1.6182***	-0.5848***	-0.8970***	-0.5125***	-0.7867 ***
	(0.0248)	(0.0528)	(0.0183)	(0.0320)	(0.0163)	(0.0267)
(*AvgnbArticle$_{t-1}$*)^2		0.0737***		0.0405***		0.0353 ***
		(0.0031)		(0.0023)		(0.0021)
ln($10^4\times$*BtwCent$_{t-2}$*)		-0.0062		0.0051		0.0124
$\times$ *NbPatent$_{t-1}$*		(0.0288)		(0.0265)		(0.0260)
ln($10^4\times$*BtwCent$_{t-2}$*)		-0.0046		-0.0054**		-0.0058 **
$\times$ (*NbPatent$_{t-1}$*)^2		(0.0029)		(0.0027)		(0.0026)
ln(*AvgContract$_{t-1}$*)		-0.0028*		-0.0027*		-0.0026 *
$\times$ *NbPatent$_{t-1}$*		(0.0016)		(0.0014)		(0.0014)
Years	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.1447***	0.3406***	0.1417***	0.3566***	0.3383***	0.3646 ***
	(0.0217)	(0.0248)	(0.0210)	(0.0228)	(0.0225)	(0.0223)
Nb of observations	16987	16987	16987	16987	16987	16987
Nb of groups	1701	1701	1701	1701	1701	1701
χ^2	1902***	1630.516***	1911.616***	1540.215***	1330.868***	1553.059 ***

Note: ***, **, * show significance at the 1%, 5% and 10% levels and standard errors are presented in parentheses. The effect of all variables where we report a non-linear effect or interactive variables without the interaction presented was tested and shown in the Appendix.

Our results provide evidence of the importance of government grants on academic publications. The estimates of our models described above demonstrate that obtaining public funding (*AvgGrant3$_{t-1}$*) increases the number of citations that these publications receive. This strong positive effect is consistent and robust for all six models. In addition, we see that while receiving private funding (*AvgContract3$_{t-1}$*) from industry yields a positive impact, the quadratic effect is negative. While 85% of our sample of researchers did not raise private funding, 99% of the remaining scientists are located on the right side of an inverted U-shaped curve, which suggests that receiving more than \$500 from industry decreases the number of citations. This threshold is rather low and as such, raising private funding is associated with a diminishing number of citations for the researcher's articles in following years.

Moreover, we investigated how the number of articles affects the number of citations, although it seems clear we would find a strongly positive effect. However, our results show a positive quadratic effect and a negative linear effect, suggesting that researchers need to have a greater number of articles to be noticed, which should in return increase their total number of citations. In our data, this threshold corresponds to 11 articles, but only 1% of scientists have produced more than 11 articles in nanotechnology.

Although involvement in patenting activities (measured by $nbPatent_{t-1}$) in previous years appears to have a positive significant effect on the number of citations of a scientist's publication, the negative sign of the quadratic effect of patenting implies that contributing to too many patents will have a diminishing returns relationship with the number of citations and eventually have a decreasing impact. The maximum amount of citations is obtained when scientists have produced a maximum of 29 patents in the past three years; contributing to fewer than this number of patents has a positive impact on the number of citations. In our data, 99.5% of scientists have fewer than 29 patents.

We generally find that a better intermediary position ($BtwCent_{t-2}$) has a significantly and consistently positive impact in all three GMM models (2, 4 and 6). In terms of being in a clustered network ($Cliqness_{t-2}$), we found a positive effect only in model 2. Researchers at the centre of the collaboration network seem to benefit from their position to gain a higher number of citations. Since research is a team activity, the collaboration patterns reflected in researchers' teams not only influence scientific output and control the amount of government funding received by team players, but also increasingly contribute to scientific output citations. It is important to note that nanotechnology research and development is highly multidisciplinary, drawing from different fields and needing extensive research teams from various departments. Scientists of greater importance undoubtedly occupy more central positions in the collaboration network. Our results show that scientists who occupy better intermediary positions produce more highly cited research. Thus, we could say that the combination of government funding and a more central position has a positive influence on research citations. While these findings generally support the assumption that research collaborations are positively associated with research production, similar to the findings of a number of scholars (Frenken et al., 2005; Lee and Bozeman, 2005; Rigby and Edler, 2005), these results are new contributions in terms of nanotechnology research citations. But more importantly, they account for the self-reinforcing effect that past citations (from the autoregressive model) and other actions in the past influence the current state of affairs.

4.2 Results of binary treatment effect (propensity score matching model)

We used propensity score matching (PSM), a statistical technique that involves twinning each scientist who received funding with one or more scientists who did not, but who in all other observable respects are similar to the funded scientist. The idea is to use a group of treated researchers, in this case those receiving grants/contracts, and a large group of non-treated researchers. We define two treatment indicators, which are dummy variables, one for grants and the other for contracts for treated and non-treated researchers. These variables take the value of 1 if the average amount of funding in our time period (1996-2005) is greater than zero, and 0 otherwise. We then take the average of our variables during the time period to run the matching procedure, which uses a logit estimation run to predict the propensity score. The Stata command *psmatch2* calculates the average treatment effect on the treated (ATT) for the entire population; the result of the procedure is the difference of ATT between the treatment and control groups. The differences between the treated and matched control groups are then assumed to be a result of the treatment. Table 2 presents the average treatment effect on the treatment estimates.

Table 2 Average Treatment effect on Treated (ATT) using psmatch2

Matching method	Sample	Treated	Controls	Difference	S.E	t-test
M(nbArtCit3)						
Treatment is public funding(Grants)						
Mahalanobis Matching with caliper	ATT	1.1858	1.1689	0.0168	(0.6273)	0.03
Treatment is private funding (Contracts)						
Mahalanobis Matching with caliper	ATT	1.1969	1.8161	-0.6192	(0.4227)	-1.46

Notes: Treatment is 1 if the average amount of funding in our time period is greater than zero, and 0 otherwise; M is the mean of variable nbArtCit3

The results of all matching methods show a positive effect from receiving public funding and a negative effect from receiving private funding on the number of citations. The difference after matching results shows that if a researcher receives a grant (of any amount), his or her number of citations rises by 0.0168 on average. However, the number of citations decreases when private funding is received. It is important to note that the estimated coefficients cannot be treated as marginal effects of explanatory variables in this model.

Once the matching of the treatment and control groups has been carried out, we need to investigate the strength of these matching methods and examine the matching quality. It is important to determine whether the resulting comparison groups are well balanced across all covariates. To assess the post-matching balance, we performed simple *t-tests* to determine whether differences remain after conditioning on the propensity score between the control and treated groups. The *pstest* command (propensity score test) in Stata compares the covariate distributions and gives *t*-test results for the pre- and post-matching samples. The results are summarized in Table 3.

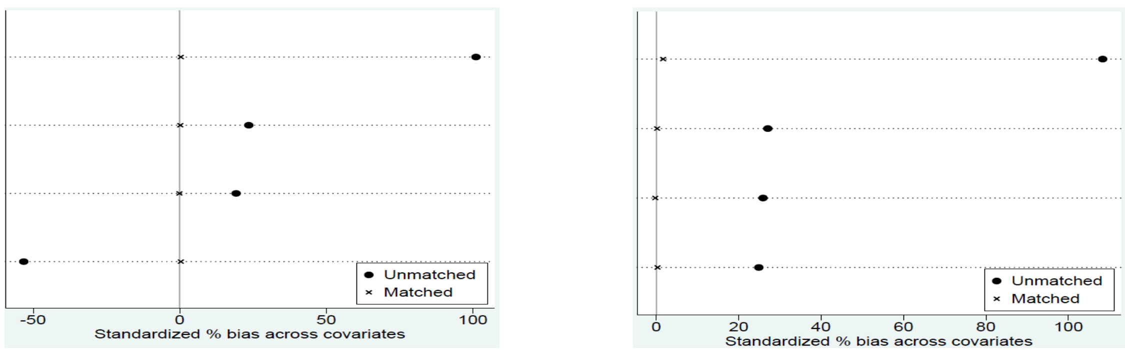
Table 3 Propensity score matching test results to assess the success of matching for grants and contracts

Variables		(1) Treatment: Grants					(2) Treatment: Contracts				
		Mean		reduct bias%	p-value		Mean		reduct bias%	p-value	
		Treated	Control				Treated	Control			
M(Contract)											
	Unmatched	3.918	0.328	99.6	0.000	***					
	Matched	0.893	0.879		0.927						
M(Grant)											
	Unmatched						10.980	7.032	98.5	0.000	***
	Matched						10.839	10.778		0.643	
M(10^3×Cliqness)											
	Unmatched	3.450	2.792	99.2	0.000	***	3.7924	3.076	99.0	0.000	***
	Matched	3.077	3.071		0.974		3.3771	3.384		0.969	
M(nbArticle)											
	Unmatched	0.247	0.181	99.5	0.003	***	0.2945	0.202	98.8	0.000	***
	Matched	0.144	0.144		0.976		0.1709	0.170		0.941	
MaxAge											
	Unmatched	14.778	17.483	99.9	0.000	***	16.2490	14.767	99.3	0.000	***
	Matched	16.310	16.313		0.991		16.371	16.360		0.974	

[1]M is the mean of variables

This *t*-test, which is carried out before and after matching, tests the hypothesis that the mean value of our variables is the same in the treatment and in the control group. It gives us a *p*-value that can allow rejection of the null hypothesis if less than 0.1 at the significance level of 10%. Furthermore, a bias and the change in this bias are calculated before and after matching. Determining the best covariate balance after matching is important to select an appropriate matching algorithm. Table 3 reflects the difference of the variables between the two groups before and after matching. By matching, the differences between the treatment group and non-treatment group are reduced considerably and the matching variables were well balanced. Even for the variables where the difference between the two groups is not eliminated by the *p*-value, we can see that the percentage of reduction bias is high.

Figure 1 shows the standardized bias across covariates for our results, highlighting that the standard bias is low for all covariates in model (1) – grants and model (2) – contracts. Accordingly, the percentage of bias is small and we can reject the hypothesis that the mean value of these two variables is not the same after matching.



Model (1) **Model (2)**

Figure 1 The standard bias across covariates in the Mahalanobis method for the impact of grants in model (1) and impact of contracts in model (2)

The potential outcomes of propensity score matching show the positive impact of grants, while the impact of contracts is negative. The results of the autoregression model also showed the positive effect of grants and a general negative impact of contracts (i.e. mainly located on the right-hand leg of the inverted U-shaped curve).

We estimated regressions on the matched sample using the observations from both the treated group and their matched untreated observations in the control group. Note that this approach uses the matched sample, which is based on the estimated propensity scores. The results of the regressions using the reduced sample composed of matched pairs (Table 4) also confirm the positive impact of public funding on the number of citations, both in terms of treatment (having raised public funding or not) and in terms of the amount raised. The results for the impact of private funding show a negative impact on citations (more detailed results are presented in Table A.6, Table A.7 and Table A.8 in the Appendix).

Table 4 Regression results over only matched pairs of researchers for matching on grants and matching on contracts -xtdpdsys

$ln(nbArtCit3_t)$	Matched Sample on Grants			Matched Sample on Contracts		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(nbArtCit3_{t-1})$	0.0828***	0.0785***	0.0494***	0.0603***	0.0646***	0.0372 **
	(0.0171)	(0.0172)	(0.0148)	(0.0179)	(0.0179)	(0.0166)
$ln(nbArtCit3_{t-2})$	0.0545***	0.0469***		0.0695***	0.0662***	
	(0.0156)	(0.0160)		(0.0168)	(0.0167)	
$ln(nbArtCit3_{t-3})$	-0.0089			-0.0135		
	(0.0162)			(0.0168)		
$\ln(AvgGrant3_{t-1})$	0.0728	-0.0593	-0.1214	0.2135***	0.2680***	0.5767 ***
	(0.0538)	(0.0806)	(0.1877)	(0.0581)	(0.0597)	(0.1472)
$\ln(AvgContract3_{t-1})$	-0.7622***	0.0000	-1.6923	-0.2707***	-0.5275	-1.4407 ***
	(0.2875)	(0.0000)	(1.1314)	(0.0447)	(0.6568)	(0.5015)
$[\ln(AvgContract_{t-1})]^2$		-0.2252***			0.0302	
		(0.0602)			(0.0682)	
$nbPatent_{t-1}$	-0.0965	-6.8622*	1.3200	-0.5845	0.0000	-7.2581 **
	(0.5148)	(3.7855)	(1.2806)	(0.4042)	(0.0000)	(2.9988)
$ln(10^4 \times BtwCent_{t-2})$	0.7439	6.2934***	4.6443*	0.2146	-2.2336	-20.2674 **
	(1.1071)	(2.2573)	(2.6809)	(0.5278)	(1.5372)	(8.2295)
$\ln(10^3 \times Cliqness_{t-2})$	-0.0179	-6.1927*	-0.0133	0.0505	6.1876	1.0458 **
	(0.0482)	(3.3179)	(0.0563)	(0.0734)	(4.0531)	(0.4359)
$AvgnbArticle_{t-1}$	-0.3046	-1.6107	-2.9952**	0.4902**	-1.5193**	-0.1619
	(0.4631)	(1.6601)	(1.4824)	(0.2062)	(0.6864)	(0.2355)
$\ln(10^4 \times BtwCent_{t-2})$		0.0000	-9.3367		0.0000	-13.5364 ***
$\times NbPatent_{t-1}$		(0.0000)	(7.8192)		(0.0001)	(4.6140)
$\ln(10^4 \times BtwCent_{t-2})$		2.3376	9.3640		0.0000	59.7325 ***
$\times (NbPatent_{t-1})^2$		(2.0423)	(7.9438)		(0.0000)	(21.6904)
$\ln(AvgContract_{t-1})$		0.0000	-88.4133***		-0.1943**	1.4453 **
$\times NbPatent_{t-1}$		(0.0001)	(18.7795)		(0.0821)	(0.6703)
$[nbPatent_{t-1}]^2$		1.8082**			-0.0861	
		(0.8156)			(0.1165)	
$[\ln(10^3 \times Cliqness_{t-2})]^2$		0.9093*			-0.9183	
		(0.4945)			(0.6042)	
$(AvgnbArticle_{t-1})^2$		-0.0672			0.8034***	
		(0.4461)			(0.2749)	
Years	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.1302	1.7650***	3.2250*	-0.8341*	-1.1115**	-0.2341
	(0.4609)	(0.6477)	(1.7669)	(0.4926)	(0.5424)	(0.7055)
Nb observations	6640	6640	6640	6290	6290	6290
Nb groups	664	664	664	629	629	629
χ^2	120.0495***	142.0595***	132.5777***	175.1726***	190.1503***	175.8191 ***

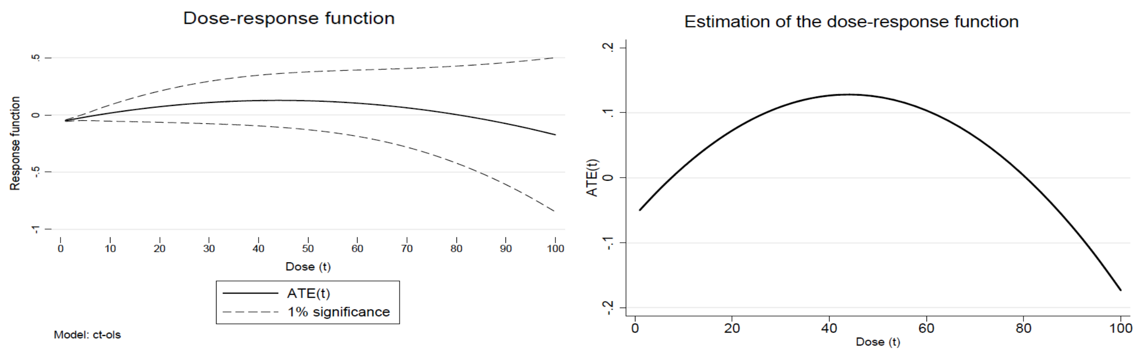
The results obtained suggest the need to extend our analysis to a continuous treatment method (rather than one using a dummy variable) to estimate the causal effect of treatments measured on a continuous level to determine the role played by the "dose" of treatment.

4.3 Results of the continuous treatment model

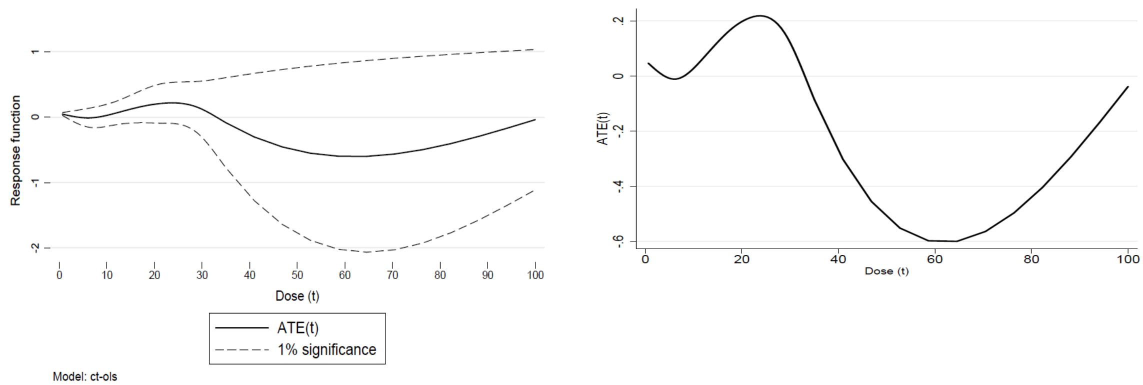
As explained above, we estimate the continuous treatment effect using lagged variables as covariates. We select the fifth year (middle year) of our 10-year panel as the base year and then we take the average amount of funding in the past three years for grants and the past five years for contracts as our treatment in the base year. We estimate the impact of raising funding (treatment variable) on the number of forward citations in the three years following publication (outcome variable) of papers published one year, two years, and three years after receiving funding.

The *ctreatreg* command in Stata calculates the Average Treatment Effect (ATE) given the level of treatment for the estimation of dose response function. This model needs to define the treatment level or dose over a range of values between 0 and 100. The value 0 specifies the treatment level on non-treated units, and the maximum dose is 100. We use the quadratic form of the treatment for public funding and the quartic form for private funding. During the course of the research, we tried linear, quadratic, cubic, quartic and higher degree polynomial functional form; the quadratic and the quartic gave the most significant and robust results.

For the continuous treatment effect, we found that funding has a significant effect (the results table is summarized in Table A.9 in the Appendix). The results presented in Figure 2 show the dose response function and the estimation of the dose response function. As these graphs indicate, the dose response function shows nonlinear behaviour with a maximum around the 40% level, which corresponds to $1.5 million and then a decline in relation to this maximum amount. Regarding the effect of private funding, the graph shows a positive impact from 10% to almost 30% of the dose corresponding to $0.7 million, then a decrease after that and an increase again of around approximately $1.5 million.



(a) Treatment is public funding



(b) Treatment is private funding

Figure 2 Continuous treatment effect of funding: the graph of dose response function and estimation of dose response function.

To address this issue, we can point to three possible effects at play here. First, researchers with private funding from industry are probably associated with applied research that may result in patent applications. Banal-Estanol et al. (2011) explained that collaborative research projects with industry are typically more applied in nature. Second, collaboration with industry may limit scientists in publishing their research outputs if the firm wants to patent the research results. Confidential content and ownership of intellectual property of the research prevent scientists from freely publishing the results as they usually do in academic research. Owen-Smith and Powell (2001) mentioned that the commercial interests of industry undermine and control university research, thus bringing a degree of secrecy to knowledge. While academic researchers tend to quickly publish their new knowledge, companies hide their findings to benefit from the research outcomes and maintain their competitive advantage (Argyres and Liebskind, 1998; Ambos et al., 2008). This may affect the quality of publications that result from privately funded research. Third, companies are generally more concerned by their industrial problems, and short-term research projects may possibly not attract the interest of researchers to use and cite the resulting publications. The second of these points can be directly addressed in our regressions by the inclusion of the number of patents as our explanatory variable.

5 Concluding Remarks

The efficacy of private and public funding for research purposes is an issue of much debate. Since previous studies generally concentrate on government funding, the literature suffers extensively from a lack of data on the impact of private research financing in universities. Moreover, the magnitude of this investment in new high technologies deserves as much consideration in order to understand the impact of funding sources on the quality of scientific production. In this paper, we set out to examine the efficiency of two different funding sources on research citations in the recently emerging and rapidly growing field of nanotechnology. To that effect, we suggested two hypotheses on nanotechnology research quality: one on public funding, the other on private funding. We found that government research funding increases the number of citations received up to three years after publication. The consistently significant results with various methods — autoregression, binary treatment effects and continuous treatment effects — all confirm that public funding has a positive impact on research citations, thereby supporting our first hypothesis. Our analysis of continuous treatment by specifying the level of funding shows that there is a threshold for grants to positively affect the citations. Although researchers that continue to receive funding will see an increase in the number of citations of their publications, it is also likely that this number may decline at some point.

While it is often argued that industry funding may limit researchers' publications, understanding the impact of private funding on the citation of these publications is more complicated. The results of this paper also fail to find a strong positive relationship providing support for our second hypothesis. First, we found a positive impact with autoregression models, but a negative quadratic effect of contracts. To further understanding, we took the average amount of funding during the 10-year data and estimated the propensity score as the probability of receiving private funding; the results showed a negative impact on citations. To analyze this impact, we switched to continuous treatment effects and observed that the relationship between private funding and the citation impact of publications is tricky and inconsistent. Several unobservable factors are at play here. While raising government funding is considered a sign of a higher quality researcher, receiving research funding from the private sector is more likely to restrict publication citation. Although industry benefits greatly from nanotechnology research, it unfortunately limits knowledge flows and generally delays publication of, or does not completely divulge, the results due to commercial issues. This problem highlights a concern about collaboration between the two different scientific worlds of academic research and commercial innovation — namely, the desire of private companies to protect their scientific outputs from being freely accessible. Accordingly, we have to reject our second hypothesis.

Results from scientific research may lay the foundation for the advancement of technologies, which may then be protected by patents in a variety of patent offices. Our examination of the influence of the number of patents to which an academic scientist has contributed in previous years shows that patenting activities do not hinder the citation of publications produced by academics. Previous literature generally considers either private funding or patents, but rarely are both measures considered together in scientific productivity or impact studies. While the former can be considered a research input and the latter a research output, our study addresses the possible influence that private endeavours may have on scientific impact from both points of view. It should also be stressed that collaboration with the private sector does not necessarily result in patents. Academics often perform consulting activities that benefit firms without there being a patent at the end of the contract. Similarly, all patents are not necessarily the result of private research investments but may also stem from government-supported scientific research. Our models consider these two possibilities by accounting for both private funding and patenting activities.

Our empirical results suggest that government grants are an important gateway to nanotechnology research development and knowledge diffusion. Publicly funded research contributes to the worldwide knowledge network and stimulates economic growth. Furthermore, this investigation shows that the relationship between public and private funding does not reinforce publication quality. While government research financing contributes to increasing the quality of knowledge being produced, and to sharing it as open science for the benefit of society, industry streams investment toward nanotechnology research to the benefit of applied research, new products and potential markets, and to the detriment of publication quality. Since the private sector is interested in short-term research, long-term and highly risky research with a potential for greater impact should accordingly be supported by government. This is not to say that academics should not seek private funding. It should be recognized that private funding is complementary in the field of nanotechnology, but serves other purposes than higher citation publications.

There are a number of limitations to this study. The first is the mobility of researchers, given that we focus on Quebec. As researchers move out of the province, we lose track of their funding. The second limitation is that because nanotechnology is an emerging and very narrow field, we may not be able to generalize to other fields. Despite these limitations, we are nevertheless confident that our results provide an interesting contribution to public versus private support of university research.

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Table A.1 – Description of dependent and explanatory variables

Variable	Description
$nbArtCit3_t$	Number of forward citations received by the papers of each scientist up to three years after publication
$AvgGrant3_{t-1}$	Average yearly amount of grants received in the past three years lagged one year
$AvgContract3_{t-1}$	Average yearly amount of contracts received in the past three years lagged one year
$nbPatent_{t-1}$	Number of patents over past three years lagged one year
$BtwCent_{t-2}$	Betweenness centrality of scientists in the three-year co-publication subnetwork lagged two years
$Cliqness_{t-2}$	Cliquishness centrality of scientists in the three-year co-publication subnetwork lagged two years
Age_t	Career age of each scientist defined as the number of years since the first paper publication
$AvgnbArticle_{t-1}$	Average number of articles over the past three years lagged one year

Table A.2 – Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$nbArtCit3_t$	8333	3.1567	16.1426	0.0000	477
$AvgGrant3_{t-1}$	8333	1.9783E+05	6.1578E+05	0.0000	1.5900E+07
$AvgContract3_{t-1}$	8333	3.6375E+04	3.1054E+05	0.0000	1.1600E+07
$nbPatent3_{t-1}$	8333	0.1543	0.9919	0.0000	43
$BtwCent_{t-2}$	8333	0.0001	0.0006	0.0000	0.0132
$Cliqness_{t-2}$	8333	0.2152	0.3786	0.0000	1.0000
Age_t	8333	11.4939	5.3221	1.0000	21
$AvgnbArticle3_{t-1}$	8333	0.4310	1.2275	0.0000	18.6667

Table A.3 – Correlation matrix

Variable		1	2	3	4	5	6	7	8
$ln(nbArtCit3_t)$	**1**	1.0000							
$ln(AvgGrant3_{t-1})$	**2**	0.0723	1.0000						
$ln(AvgContract3_{t-1})$	**3**	0.0359	0.2589	1.0000					
$nbPatent_{t-1}$	**4**	0.0877	0.0460	0.0789	1.0000				
$ln(10^4xBtwCent3_{t-2})$	**5**	0.3418	0.0548	0.0346	0.0779	1.0000			
$ln(10^3xCliqness3_{t-2})$	**6**	0.2195	0.0630	0.0321	0.0910	0.2999	1.0000		
Age_t	**7**	0.0535	0.3991	0.2144	0.0616	0.0562	0.1267	1.0000	
$AvgnbArticle3_{t-1}$	**8**	0.64628	0.0839	0.0320	0.0955	0.6470	0.4017	0.0909	1.0000

Table A.4 – GMM regression results of autoregressive model using hierarchical structure – *xtpdsys*

ln(nbArtCit3$_t$)	GMM-lag3 **(1)**	GMM-lag3 **(2)**	GMM-lag3 **(3)**	GMM-lag2 **(4)**	GMM-lag2 **(5)**	GMM-lag2 **(6)**	GMM-lag1 **(7)**	GMM-lag1 **(8)**	GMM-lag1 **(9)**
ln(nbArtCit3$_{t-1}$)	0.1910***	0.2523***	0.4541***	0.0886***	0.0898***	0.1129***	0.0870***	0.0879***	0.0957***
	(0.0155)	(0.0157)	(0.0220)	(0.0116)	(0.0116)	(0.0132)	(0.0089)	(0.0089)	(0.0098)
ln(nbArtCit3$_{t-2}$)	0.1492***	0.1958***	0.3658***	0.0396***	0.0401***	0.0550***			
	(0.0157)	(0.0160)	(0.0205)	(0.0113)	(0.0113)	(0.0117)			
ln(nbArtCit3$_{t-3}$)	0.1562***	0.1911***	0.3481***						
	(0.0149)	(0.0153)	(0.0191)						
ln(*AvgGrant3$_{t-1}$*)	0.0046	0.0082***	0.0102***	0.0057**	0.0056**	0.0072**	0.0100***	0.0100***	0.0114***
	(0.0029)	(0.0030)	(0.0032)	(0.0029)	(0.0029)	(0.0028)	(0.0029)	(0.0029)	(0.0029)
ln(*AvgContract3$_{t-1}$*)	0.0023	0.0059*	0.0500***	0.0028	0.0036	0.0310**	0.0059*	0.0068**	0.0395**
	(0.0035)	(0.0036)	(0.0174)	(0.0034)	(0.0034)	(0.0156)	(0.0034)	(0.0034)	(0.0157)
[ln(*AvgContract$_{t-1}$*)]^2			-0.0044***			-0.0027*			-0.0033**
			(0.0017)			(0.0015)			(0.0015)
nbPatent$_{t-1}$	0.0341***	0.0653***	0.0985***	0.0374***	0.0575***	0.0680***	0.0476***	0.0731***	0.1121***
	(0.0112)	(0.0155)	(0.0242)	(0.0108)	(0.0146)	(0.0217)	(0.0109)	(0.0147)	(0.0218)
[*nbPatent$_{t-1}$*]^2			-0.0021***			-0.0010*			-0.0020***
			(0.0006)			(0.0006)			(0.0006)
ln(10^4×*BtwCent$_{t-2}$*)	0.0547**	0.0869***	0.0835***	0.0451*	0.0459*	0.0396	0.0690***	0.0679***	0.0436
	(0.0239)	(0.0259)	(0.0297)	(0.0232)	(0.0244)	(0.0265)	(0.0233)	(0.0245)	(0.0267)
ln(10^3×*Cliqness$_{t-2}$*)	-0.0051	0.0028	0.1373*	0.0026	0.0027	-0.0378	0.0149***	0.0150***	0.0372
	(0.0039)	(0.0040)	(0.0776)	(0.0037)	(0.0037)	(0.0696)	(0.0037)	(0.0037)	(0.0697)
[ln(10^3×*Cliqness$_{t-2}$*)]^2			-0.0185*			0.0063			-0.0032
			(0.0112)			(0.0101)			(0.0101)
AvgnbArticle$_{t-1}$	-0.7532***	-0.7690***	-1.6126***	-0.5848***	-0.5854***	-0.9163***	-0.5125***	-0.5128***	-0.7833***
	(0.0248)	(0.0256)	(0.0527)	(0.0183)	(0.0183)	(0.0312)	(0.0163)	(0.0163)	(0.0267)
(AvgnbArticle$_{t-1}$)^2			0.0733***			0.0403***			0.0349***
			(0.0031)			(0.0022)			(0.0021)
ln(10^4×*BtwCent$_{t-2}$*)		0.0150			0.0076			0.0189	
× *NbPatent$_{t-1}$*		(0.0270)			(0.0254)			(0.0257)	
ln(10^4×*BtwCent$_{t-2}$*)		-0.0033			-0.0025			-0.0043*	
× *(NbPatent$_{t-1}$)^2*		(0.0027)			(0.0026)			(0.0026)	
ln(*AvgContract$_{t-1}$*)		-0.0037**			-0.0030**			-0.0036***	
× *NbPatent$_{t-1}$*		(0.0015)			(0.0014)			(0.0014)	
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.1447***	0.3168***	0.3435***	0.1417***	0.1403***	0.1581***	0.3383***	0.3357***	0.3673***
	(0.0217)	(0.0237)	(0.0247)	(0.0210)	(0.0210)	(0.0209)	(0.0225)	(0.0225)	(0.0223)
Nb observations	16987	16987	16987	16987	16987	16987	16987	16987	16987
Nb groups	1701	1701	1701	1701	1701	1701	1701	1701	1701
χ^2	1902***	1393.261***	1622.271***	1911.616***	1914.894***	2204.574***	1330.868***	1337.745***	1542.298***

Table A.5 – Robust regression results of autoregressive model using hierarchical structure – *xtpdsys*

ln(nbArtCit3$_t$)	Robust-lag3 (1)	Robust -lag3 (2)	Robust -lag3 (3)	Robust -lag2 (4)	Robust -lag2 (5)	Robust -lag2 (6)	Robust -lag1 (7)	Robust -lag1 (8)	Robust -lag1 (9)
ln(nbArtCit3$_{t-1}$)	0.1910***	0.2523***	0.4541***	0.0886**	0.0898**	0.1129***	0.0870***	0.0879 ***	0.0957 ***
	(0.0622)	(0.0592)	(0.0567)	(0.0356)	(0.0359)	(0.0291)	(0.0229)	(0.0231)	(0.0217)
ln(nbArtCit3$_{t-2}$)	0.1492**	0.1958***	0.3658***	0.0396	0.0401	0.0550**			
	(0.0593)	(0.0570)	(0.0565)	(0.0301)	(0.0302)	(0.0258)			
ln(nbArtCit3$_{t-3}$)	0.1562***	0.1911***	0.3481***						
	(0.0481)	(0.0467)	(0.0472)						
ln(*AvgGrant3$_{t-1}$*)	0.0046	0.0082**	0.0102***	0.0057	0.0056	0.0072**	0.0100***	0.0100 ***	0.0114 ***
	(0.0037)	(0.0036)	(0.0037)	(0.0036)	(0.0036)	(0.0034)	(0.0036)	(0.0036)	(0.0034)
ln(*AvgContract3$_{t-1}$*)	0.0023	0.0059	0.0500**	0.0028	0.0036	0.0310*	0.0059	0.0068 *	0.0395 **
	(0.0039)	(0.0040)	(0.0200)	(0.0038)	(0.0038)	(0.0187)	(0.0038)	(0.0038)	(0.0186)
[ln(*AvgContract$_{t-1}$*)]^2			-0.0044**			-0.0027			-0.0033 *
			(0.0020)			(0.0019)			(0.0018)
nbPatent$_{t-1}$	0.0341**	0.0653**	0.0985***	0.0374**	0.0575**	0.0680**	0.0476***	0.0731 ***	0.1121 ***
	(0.0173)	(0.0269)	(0.0371)	(0.0158)	(0.0229)	(0.0344)	(0.0168)	(0.0231)	(0.0351)
[*nbPatent$_{t-1}$*]^2			-0.0021*			-0.0010			-0.0020 **
			(0.0011)			(0.0009)			(0.0009)
ln(10^4×*BtwCent$_{t-2}$*)	0.0547	0.0869*	0.0835	0.0451	0.0459	0.0396	0.0690*	0.0679	0.0436
	(0.0433)	(0.0486)	(0.0515)	(0.0409)	(0.0455)	(0.0460)	(0.0391)	(0.0431)	(0.0454)
ln(10^3×*Cliqness$_{t-2}$*)	-0.0051	0.0028	0.1373	0.0026	0.0027	-0.0378	0.0149**	0.0150 **	0.0372
	(0.0073)	(0.0071)	(0.1430)	(0.0077)	(0.0076)	(0.1278)	(0.0075)	(0.0075)	(0.1298)
[ln(10^3×*Cliqness$_{t-2}$*)]^2			-0.0185			0.0063			-0.0032
			(0.0206)			(0.0185)			(0.0188)
AvgnbArticle$_{t-1}$	-0.7532***	-0.7690***	-1.6126***	-0.5848***	-0.5854***	-0.9163***	-0.5125***	-0.5128 ***	-0.7833 ***
	(0.1204)	(0.1202)	(0.1496)	(0.0690)	(0.0694)	(0.0649)	(0.0529)	(0.0531)	(0.0557)
(AvgnbArticle$_{t-1}$)^2			0.0733***			0.0403***			0.0349 ***
			(0.0094)			(0.0042)			(0.0041)
ln(10^4×*BtwCent$_{t-2}$*)		0.0150			0.0076			0.0189	
× *NbPatent$_{t-1}$*		(0.0448)			(0.0427)			(0.0404)	
ln(10^4×*BtwCent$_{t-2}$*)		-0.0033			-0.0025			-0.0043	
× (*NbPatent$_{t-1}$*)^2		(0.0043)			(0.0039)			(0.0039)	
ln(*AvgContract$_{t-1}$*)		-0.0037			-0.0030			-0.0036 *	
× *NbPatent$_{t-1}$*		(0.0023)			(0.0022)			(0.0020)	
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.1447***	0.3168***	0.3435***	0.1417***	0.1403***	0.1581***	0.3383***	0.3357 ***	0.3673 ***
	(0.0281)	(0.0369)	(0.0348)	(0.0276)	(0.0276)	(0.0264)	(0.0333)	(0.0332)	(0.0325)
Nb observations	16987	16987	16987	16987	16987	16987	16987	16987	16987
Nb groups	1701	1701	1701	1701	1701	1701	1701	1701	1701
χ^2	330.42	216.521	323.5201	354.669	365.2675	515.846	251.578	258.712	388.098 ***

Table A.6 Regression results over only matched pairs of researchers for matching on grants and matching on contracts – xtreg

ln(nbArtCit3$_t$)	Matched Sample on Grants			Matched Sample on Contracts		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(*AvgGrant3$_{t-1}$*)	0.0035**	0.0036**	0.0034**	0.0034	0.0035	0.0039 *
	(0.0015)	(0.0015)	(0.0015)	(0.0024)	(0.0024)	(0.0023)
ln(*AvgContract3$_{t-1}$*)	-0.0123***	-0.0123***	-0.0115	-0.0069***	-0.0068***	-0.0158
	(0.0039)	(0.0040)	(0.0375)	(0.0022)	(0.0023)	(0.0112)
[ln(*AvgContract$_{t-1}$*)]^2			-0.0001			0.0008
			(0.0040)			(0.0011)
nbPatent$_{t-1}$	0.0194	0.0143	-0.0284	-0.0052	-0.0065	-0.0194
	(0.0168)	(0.0175)	(0.0399)	(0.0141)	(0.0209)	(0.0319)
ln(10^4×BtwCent$_{t-2}$)	0.0629**	0.0952***	0.0552*	0.0012	0.0008	-0.0918 *
	(0.0247)	(0.0292)	(0.0325)	(0.0439)	(0.0448)	(0.0539)
ln(10^3×*Cliqness$_{t-2}$*)	0.0135***	0.0128***	0.2570***	0.0247***	0.0247***	0.4170 ***
	(0.0031)	(0.0031)	(0.0788)	(0.0040)	(0.0041)	(0.0845)
AvgnbArticle$_{t-1}$	0.2901***	0.2903***	0.3505***	0.3130***	0.3145***	0.3954 ***
	(0.0161)	(0.0160)	(0.0344)	(0.0230)	(0.0232)	(0.0457)
ln(10^4×*BtwCent$_{t-2}$*)		-0.2776***	-0.2438***		-0.1667	-0.3440
× *NbPatent$_{t-1}$*		(0.0891)	(0.0885)		(0.2513)	(0.2492)
ln(10^4×*BtwCent$_{t-2}$*)		0.1803***	0.1671***		0.1030	0.1697
×(*NbPatent$_{t-1}$)^2*		(0.0650)	(0.0646)		(0.1144)	(0.1124)
ln(*AvgContract$_{t-1}$*)		-0.0002	0.0035		-0.0001	-0.0019
× *NbPatent$_{t-1}$*		(0.0216)	(0.0227)		(0.0031)	(0.0033)
[*nbPatent$_{t-1}$*]^2			0.0114			0.0029
			(0.0094)			(0.0048)
[ln(10^3×*Cliqness$_{t-2}$*)]^2			-0.0360***			-0.0579 ***
			(0.0114)			(0.0123)
(AvgnbArticle$_{t-1}$)^2			-0.0219***			-0.0370 ***
			(0.0074)			(0.0132)
Years	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.0145	0.0145	0.0121	0.0177	0.0163	0.0107
	(0.0265)	(0.0264)	(0.0265)	(0.0335)	(0.0336)	(0.0333)
Nb observations	6640	6640	6640	6300	6290	6290
Nb groups	664	664	664	629	629	629
χ^2	799.0703***	816.3977***	852.5344***	517.8856***	517.2222***	574.4732 ***

Table A.7 Regression results on dummy treatment of public and private funding – xtreg

ln(nbArtCit3$_t$)	**(1)**	**(2)**	**(3)**	**(4)**
ln(*AvgGrant3$_{t-1}$*)		0.0055*** (0.0011)		0.0051 *** (0.0012)
ln(*AvgContract3$_{t-1}$*)	0.0037 (0.0087)			0.0047 (0.0088)
[ln(*AvgContract$_{t-1}$*)]^2	-0.0002 (0.0008)			-0.0002 (0.0008)
nbPatent$_{t-1}$	0.0642*** (0.0109)	0.0646*** (0.0108)	0.0652*** (0.0108)	0.0642 *** (0.0109)
[*nbPatent$_{t-1}$*]^2	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0017*** (0.0004)	-0.0016 *** (0.0004)
ln(10^4×*BtwCent$_{t-2}$*)	0.0597*** (0.0193)	0.0581*** (0.0193)	0.0594*** (0.0193)	0.0586 *** (0.0193)
ln(10^3×*Cliqness$_{t-2}$*)	0.3145*** (0.0488)	0.3163*** (0.0488)	0.3172*** (0.0488)	0.3133 *** (0.0488)
[ln(10^3×*Cliqness$_{t-2}$*)]^2	-0.0462*** (0.0071)	-0.0464*** (0.0071)	-0.0466*** (0.0071)	-0.0460 *** (0.0071)
AvgnbArticle$_{t-1}$	0.4511*** (0.0161)	0.4483*** (0.0161)	0.4487*** (0.0161)	0.4500 *** (0.0161)
(*AvgnbArticle$_{t-1}$*)^2	-0.0165*** (0.0013)	-0.0164*** (0.0013)	-0.0164*** (0.0013)	-0.0165 *** (0.0013)
dtreated_public	0.0700*** (0.0127)		0.0741*** (0.0126)	
dtreated_private		0.0158 (0.0184)	0.0088 (0.0185)	
Years	Yes	Yes	Yes	Yes
Constant	0.0580*** (0.0194)	0.0609*** (0.0196)	0.0588*** (0.0194)	0.0610 *** (0.0196)
Nb of observations	17000	17000	17000	17000
Nb of groups	1701	1701	1701	1701
χ^2	4638.758***	4555.102***	4588.03***	4581.036 ***

Table A.8 Regression results on dummy treatment of public and private funding _xtdpdsys

ln(nbArtCit3$_t$)	**(1)**	**(2)**	**(3)**	**(4)**
ln(nbArtCit3$_{t-1}$)	0.3763*** (0.0216)	0.3781*** (0.0216)	0.3793*** (0.0216)	0.3755 *** (0.0216)
ln(nbArtCit3$_{t-2}$)	0.3062*** (0.0200)	0.3089*** (0.0201)	0.3093*** (0.0201)	0.3060 *** (0.0200)
ln(nbArtCit3$_{t-3}$)	0.3032*** (0.0186)	0.3046*** (0.0187)	0.3054*** (0.0186)	0.3026 *** (0.0186)
ln(*AvgGrant3$_{t-1}$*)		0.0066** (0.0030)		0.0064 ** (0.0031)
ln(*AvgContract3$_{t-1}$*)	0.0380** (0.0169)			0.0381 ** (0.0169)
[ln(*AvgContract$_{t-1}$*)]^2	-0.0034** (0.0016)			-0.0035 ** (0.0016)
nbPatent$_{t-1}$	0.0623*** (0.0234)	0.0607*** (0.0235)	0.0623*** (0.0235)	0.0608 *** (0.0234)
[*nbPatent$_{t-1}$*]^2	-0.0011* (0.0006)	-0.0011* (0.0006)	-0.0011* (0.0006)	-0.0011 * (0.0006)
ln($10^4\times$*BtwCent$_{t-2}$*)	0.0730** (0.0287)	0.0815*** (0.0287)	0.0832*** (0.0287)	0.0715 ** (0.0287)
ln($10^3\times$*Cliqness$_{t-2}$*)	0.0194 (0.0752)	-0.0071 (0.0748)	-0.0104 (0.0748)	0.0222 (0.0752)
[ln($10^3\times$*Cliqness$_{t-2}$*)]^2	-0.0026 (0.0109)	0.0012 (0.0108)	0.0017 (0.0108)	-0.0030 (0.0109)
AvgnbArticle$_{t-1}$	-1.5353*** (0.0510)	-1.5382*** (0.0511)	-1.5341*** (0.0510)	-1.5398 *** (0.0511)
(*AvgnbArticle$_{t-1}$*)^2	0.0690*** (0.0030)	0.0694*** (0.0030)	0.0692*** (0.0030)	0.0692 *** (0.0030)
dtreated_public	0.0287 (0.0271)		0.0266 (0.0273)	
dtreated_private		0.0365 (0.0304)	0.0373 (0.0305)	
Years	Yes	Yes	Yes	Yes
Constant	0.2127*** (0.0220)	0.1882*** (0.0247)	0.2145*** (0.0215)	0.1903 *** (0.0247)
Nb of observations	17000	16997	17010	16987
Nb of groups	1701	1701	1701	1701
χ^2	2053.353***	2038.166***	2029.972***	2060.898 ***

Table A.9 – Continuous treatment effect for funding on the number of citations as outcome variable

Variables	Treatment is Public funding	Treatment is Private funding
Treatment_Grant	-0.0446 ** -(0.0215)	
Treatment_Contract		0.0593 ** (0.0275)
Treatment_GrantContract		
(AvgGrant3$_{baseyear-4}$)		
(AvgGrant3$_{baseyear-3}$)		
AvgGrant3$_{baseyear-2}$)		0.0000 ** (0.0000)
(AvgGrant3$_{baseyear-1}$)		0.0000 (0.0000)
(AvgGrant3$_{baseyear}$)		0.0000 (0.0000)
(AvgGrant3$_{baseyear+1}$)		0.0000 (0.0000)
(AvgGrant3$_{baseyear+2}$)		0.0000 (0.0000)
(AvgGrant3$_{baseyear+3}$)		0.0000 *** (0.0000)
(AvgGrant3$_{baseyear+4}$)		0.0000 (0.0000)
(AvgContract3$_{baseyear-4}$)	-2.18E-07 (4.58E-07)	
(AvgContract3$_{baseyear-3}$)	0.6338	
(AvgContract3$_{baseyear-2}$)	-1.82E-07 (8.52E-07)	
(AvgContract3$_{baseyear-1}$)	0.8307	
(AvgContract3$_{baseyear}$)	1.42E-06 ** (6.77E-07)	
(AvgContract3$_{baseyear+1}$)	0.0355	
(AvgContract3$_{baseyear+2}$)	-9.74E-07 (9.30E-07)	
(AvgContract3$_{baseyear+3}$)	0.2947	
(AvgContract3$_{baseyear+4}$)	-2.23E-07 (1.26E-06)	
ln(10^4×BtwCent $_{baseyear-4}$)	-0.0597 * -(0.0361)	
ln(10^4×BtwCent $_{baseyear-3}$)	0.0076 -(0.0409)	-0.0228 (0.0298)
ln(10^4×BtwCent $_{baseyear-2}$)	-0.0446 -(0.0363)	0.0046 (0.0342)
ln(10^4×BtwCent $_{baseyear-1}$)	-0.1082 *** -(0.0385)	-0.1098 *** (0.0379)
ln(10^4×BtwCent $_{baseyear}$)	0.0238 -(0.0405)	0.0194 (0.0391)
ln(10^4×BtwCent $_{baseyear+1}$)	0.0215 -(0.0392)	0.0255 (0.0391)

$ln(10^4 \times BtwCent_{baseyear+2})$	-0.1132	**	-0.1093	**
	-(0.0444)		(0.0443)	
$ln(10^4 \times BtwCent_{baseyear+3})$	0.1256	***	0.1135	***
	-(0.0433)		(0.0426)	
$ln(10^4 \times BtwCent_{baseyear+4})$	-0.0310		-0.0184	
	-(0.0302)		(0.0278)	
$ln(10^3 \times Cliqness_{baseyear-4})$	0.0027			
	-(0.0061)			
$ln(10^3 \times Cliqness_{baseyear-3})$	-0.0039			
	-(0.0079)			
$ln(10^3 \times Cliqness_{baseyear-2})$	-0.0052		0.0085	
	-(0.0083)		(0.0061)	
$ln(10^3 \times Cliqness_{baseyear-1})$	0.0006		-0.0057	
	-(0.0086)		(0.0076)	
$ln(10^3 \times Cliqness_{baseyear})$	-0.0082		-0.0026	
	-(0.0081)		(0.0071)	
$ln(10^3 \times Cliqness_{baseyear+1})$	-0.0031		-0.0041	
	-(0.0081)		(0.0078)	
$ln(10^3 \times Cliqness_{baseyear+2})$	0.0065		0.0034	
	-(0.0077)		(0.0076)	
$ln(10^3 \times Cliqness_{baseyear+3})$	0.0108		0.0095	
	-(0.0073)		(0.0068)	
$ln(10^3 \times Cliqness_{baseyear+4})$	-0.0067		-0.0045	
	-(0.0057)		(0.0047)	
$ln(nbPatent_{baseyear-4})$	0.0210		0.0543	
	-(0.0821)		(0.0814)	
$ln(nbPatent_{baseyear-3})$	-0.2520	***	-0.2368	**
	-(0.0974)		(0.0970)	
$ln(nbPatent_{baseyear-2})$	-0.1289	*	-0.1252	*
	-(0.0762)		(0.0759)	
$ln(nbPatent_{baseyear-1})$	0.0624		0.0562	
	-(0.0739)		(0.0742)	
$ln(nbPatent_{baseyear})$	0.0840		0.0552	
	-(0.0717)		(0.0716)	
$ln(nbPatent_{baseyear+1})$	0.1324	*	0.1133	
	-(0.0768)		(0.0762)	
$ln(nbPatent_{baseyear+2})$	0.0366		0.0459	
	-(0.0635)		(0.0630)	
$ln(nbPatent_{baseyear+3})$	0.0126		-0.0031	
	-(0.0732)		(0.0730)	
$ln(nbPatent_{baseyear+4})$	-0.1002		-0.1182	
	-(0.0851)		(0.0846)	
$ln(nbArticle_{baseyear-4})$	0.1312	***		
	-(0.0422)			
$ln(nbArticle_{baseyear-3})$	0.0146			
	-(0.0441)			
$ln(nbArticle_{baseyear-2})$	0.1024	**		
	-(0.0408)			
$ln(nbArticle_{baseyear-1})$	0.1535	***	0.1755	***
	-(0.0392)		(0.0376)	
$ln(nbArticle_{baseyear})$	0.0149		0.0222	
	-(0.0392)		(0.0378)	
$ln(nbArticle_{baseyear+1})$	1.5826	***	1.5984	***
	-(0.0373)		(0.0356)	
$ln(nbArticle_{baseyear+2})$	-0.0754	**	-0.0591	
	-(0.0375)		(0.0371)	
$ln(nbArticle_{baseyear+3})$	-0.0891	***	-0.0790	**
	-(0.0333)		(0.0328)	

ln(nbArticle $_{baseyear+4}$*)*	0.0228	
	-(0.0287)	
ln(Age $_{baseyear-4}$*)*	0.0479	0.0629
	-(0.0697)	(0.0675)
ln(Age $_{baseyear-3}$*)*	0.1123	0.0838
	-(0.1457)	(0.1423)
ln(Age $_{baseyear-2}$*)*	-0.3211 **	-0.2958 *
	-(0.1588)	(0.1578)
ln(Age $_{baseyear-1}$*)*	0.1689	0.2063
	-(0.1588)	(0.1583)
ln(Age $_{baseyear}$*)*	-0.0619	-0.1157
	-(0.1707)	(0.1697)
ln(Age $_{baseyear+1}$*)*	0.0515	0.0502
	-(0.1687)	(0.1685)
ln(Age $_{baseyear+2}$*)*	-0.0043	0.0016
	-(0.1904)	(0.1901)
ln(Age $_{baseyear+3}$*)*	0.0063	0.0034
	-(0.2005)	(0.2000)
ln(Age $_{baseyear+4}$*)*	0.0008	0.0044
	-(0.1176)	(0.1174)
Tw1	0.0085 **	-0.0340 *
	-(0.0038)	(0.0204)
Tw2	-0.0001 *	0.0042 *
	(0.0000)	(0.0023)
Tw3		-0.0001 *
		(0.0001)
Tw4		0.0000 *
		(0.0000)
Constant	0.0000	0.0000
	-(0.0846)	(0.0844)
Nb observations	1701	1701
R^2	0.7509	0.7508
F-statistics	86.87 ***	99.37 ***

Note: ***, **, * show significance at the 1%, 5% and 10% levels and standard errors are presented in parentheses.