Open Science as a Signaling Device: Evidence from Firm Publications*

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Abstract

This paper empirically investigates the practice of private firms to publish in academic journals. Using a novel and comprehensive dataset for European firms, we find that firms contribute substantially to the advancement of basic scientific knowledge. Young firms with a short track record appear to be more publication intensive than mature firms. This difference is amplified in industries where performance varies substantially across firms and in countries where financial markets are highly developed. Young firms are also more patent intensive than mature firms but not disproportionately so in more heterogeneous industries and in more developed financial markets. These findings are consistent with the predictions of a theoretical model where academic publications certify the quality of a firm's R&D to prospective investors.

Keywords: Open Science, Publications, Patents, Certification, Capital Markets

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1. Introduction

Few economists would disagree with the claim that economic growth is to a large extent driven by scientific and technological progress. There also seems to be some consensus on the idea that in many industries such as pharmaceuticals, electronics and IT, scientific knowledge is becoming an increasingly important part of the innovation process (Gambardella, 1995; Cockburn and Henderson, 1998; Yusuf, 2008). Yet, our understanding of the links between science and industry remains limited, having been restricted mainly to case study evidence until quite recently (Stephan, 1996).

The present paper contributes to our understanding of the science-industry relationship by empirically investigating the practice of private firms to publish in academic journals. A fundamental question in the literature is whether private companies contribute to the advancement of basic scientific knowledge. The traditional emphasis on the appropriability of the returns from R&D suggests that firms should not freely disclose their research results for fear that this information might benefit competitors. Cohen et al. (2000), in particular, provide survey evidence that firms often rely on secrecy to protect their proprietary knowledge.

More recently, however, scholars have emphasized the benefits of engaging in 'open science'. Koenig (1983), for instance, reports consistent correlations between the drug output of large pharmaceutical companies and bibliometric variables (especially highly cited clinical articles). Hicks (1995) and Hicks et al. (1996) focus on a select group of pharmaceutical, chemical and electronics firms in Europe and Japan. They show that these firms collaborate extensively with universities and other public sector laboratories and publish widely in academic journals. Similar findings are reported for the US by Stephan (1996). In the pharmaceutical industry, strong correlations between measures of connectedness with the wider scientific community and firms' internal organization and performance in drug discovery have been documented by Cockburn and Henderson (1998).

While this evidence points to significant benefits to engaging in open science, how exactly these benefits accrue remains debated. A point often stressed in the literature is that firms may conduct basic research in-house to better monitor and evaluate research conducted elsewhere (Cohen and Levinthal, 1989; Gambardella, 1992). In particular, publishing in academic journals may be the most effective way to remain 'plugged in' to the external scientific network (Rosenberg, 1990; Cockburn and Henderson, 1998). A second possibility is that scientists might have a preference for engaging in open science. To the extent that allowing scientists to publish helps firms recruit talented researchers, openness may be a profitable strategy for some firms (Stern, 2004). Third, firms may disclose their research results to establish new prior art and therefore reduce the patentability of related innovations by competitors (Baker and Mezzetti, 2005; Bar, 2006). Finally, firms may publish in academic journals to enhance their reputation and certify the quality of their research. In particular, the scientific validation provided by academic publications could help them raise external funds (Nelson, 1990; Audretsch and Stephan, 1996; Stephan, Higgins and Thursby, 2007) or win government contracts (Lichtenberg, 1986, 1988). For instance, the German biotechnology company MediGene was recently awarded a research grant of approximately 600,000 Euros from the Federal Ministry of Education and Research to engage in innovation "in the field of top-level research". It is likely that the Ministry took MediGene's impressive track record in basic research into account when making this decision.[1]

These explanations are obviously not mutually exclusive. Pharmaceutical companies often invest in new biotechnology firms (NBFs) to acquire expertise in certain technological areas (Arora and Gambardella, 1990). This 'absorptive capacity' story could easily give rise to signaling incentives, since NBFs may publish in academic journals to signal their competence and become more attractive targets. Similarly, firms may have an incentive to publish in order to enhance their scientific reputation and attract qualified employees (Nelson, 1990; Audretsch and Stephan, 1996; Stern, 2004).[2]

The present paper contributes to this literature by developing new systematic data on firm publications. We matched European firms by name (using authors' affiliations) to the complete Thomson's ISI Web of Science, which covers about 20 million publications in thousands of international journals in 'hard' sciences, such as physics and biochemistry. (For

[1] A quick search in the Web of Science database yields a total of 98 articles where at least one of the authors is a MediGene employee. See Figure A1 for an example of a MediGene publication.

[2] It should also be noted that the fact that some firms appear to benefit from disclosure does not imply that appropriability considerations are unimportant. Many innovating firms systematically screen their publications to minimize the risk that this information might benefit competitors (Koening, 1983). Furthermore, publications appear to be prevalent in sectors such as pharmaceuticals where patents provide strong protection against expropriation (Gambardella, 1995).

an example of firm publication, see Figure A1.) Financial information is from Amadeus, a dataset of about 8 million European firms covering a wide distribution of firm age and size. For each publication we have information on the number of times it has been cited as well as on the quality of the journal in which the article was published, which we use to control for the quality of publications.

Our evidence supports the view that private firms contribute substantially to the advancement of basic scientific knowledge. We matched more than 230 thousand publications to firms over the period 1970-2004. The trend is clearly upward, with the number of firm publications per year more than quadrupling over the last 20 years in most technology areas. We then study how the propensity to publish varies with firm age, measured by the number of years elapsed since the date of incorporation. Firm age is a commonly used proxy for asymmetric information between the firm and the market, suggesting that younger firms might have a greater need to establish a reputation (e.g., Ritter, 1984; Oliner and Rudebusch, 1992; Gompers, 1995). We find that, conditional on firm size (measured by lagged sales), young firms publish substantially more than mature firms. Furthermore, young firms publish disproportionately more in more heterogeneous industries and in countries with more developed financial markets. These results are robust to a variety of controls and different empirical measures of our theoretical concepts. The same broad patterns of results emerge, for instance, when we control for nonlinear effects in firm size or publication quality, or when we restrict attention to a subset of firms that recently raised external finance.

These findings are consistent with the predictions of a theoretical model where academic publications certify (or signal) the quality of a firm's research to prospective investors. Reputational concerns should in fact be particularly prominent when information asymmetries are large (as is typically the case for young firms) and performance varies substantially across firms. The scientific validation provided by academic publications may also be particularly valuable in highly developed financial markets since only competent investors may have the ability or expertise to evaluate research very close to the basic science end of the spectrum.

However, there are some important caveats concerning our empirical specification and the use of firm age that should be mentioned from the outset. First, the date of incorporation may be affected by legal changes in ownership structure such as mergers and acquisitions.

To mitigate this concern, we manually examine, using public information sources, the actual date of incorporation of the leading innovating firms in our sample. We drop firms from the analysis if their age does not correspond to the date of incorporation from Amadeus.[3] Second, firm life cycle considerations may suggests that firms devote a larger fraction of their resources to R&D early in their life. Thus young firms may be more publication intensive than mature firms just because their sales and marketing units are smaller, not because of signaling. Nevertheless, we would not expect these life cycle considerations to vary systematically with exogenous industry and country characteristics. Thus the finding that young firms publish disproportionately more in more heterogeneous industries and in countries where financial institutions are more developed, while consistent with signaling, is less easy to rationalize as a consequence of the firm life cycle hypothesis.

Finally, we use firm-level data on patents from the European Patent Office (EPO) to test for the possibility that patents may also perform a signaling function. Survey evidence suggests in fact that firms sometimes patent for reputational reasons (Cohen et al., 2000) and to attract venture capital (Hall and Ziedonis, 2001).[4] As for publications, we find that young firms are more patent intensive than mature firms; however, the interaction coefficients of firm age with industry heterogeneity and financial development are now insignificant. Thus, for instance, young firms do not appear to patent disproportionately more than mature firms in more heterogeneous industries. One explanation could be that young firms always have very strong incentives to patent regardless of industry and country conditions because by doing so they also protect their intellectual assets (these incentives are also captured in our model). The different pattern of results between patents and publications is also reassuring since it suggests that our findings are unlikely to be driven exclusively by common factors such as technological opportunity.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework motivating the empirical analysis. Sections 3 and 4 describe the data and provide descriptive statistics. Section 5 discusses our econometric specification, while Section 6

[3] More details are provided in the data section.

[4] In their survey, Cohen et al. (2000) find that smaller firms are significantly (at .01 confidence level) more likely to report the motive "to enhance the reputation of the firm or its employees" as a reason to patent. They argue that this could be rationalized "by the need of smaller firms in some high technology industries to hold patents in order to acquire financing or alliance partners" (p. 24).

reports the results. Section 7 concludes.

2. Theory

This section develops a simple model of corporate financing under adverse selection where firms can signal their competence to investors by publishing in academic journals. Our goal is to derive and discuss the empirical hypotheses that will be tested in the empirical part.

We consider an economy populated by a continuum of firms (or entrepreneurs), each seeking to finance a project costing I. All agents are risk neutral and the interest rate in the economy is normalized to 0. Firms are either innovative ('good') or traditional ('bad'), with equal probability. The profits of an innovative firm are $\alpha V(I)$ if the project is financed and $\alpha V(0)$ if the project is not financed. The corresponding profits for a traditional firm are $V(I)$ and $V(0)$ respectively. Thus $\alpha > 1$ parametrizes the difference in productivity between good and bad firms. We assume that $\alpha(V(I) - V(0)) > I$ so that it is efficient for good firms to invest.

Firms also differ in terms of their age. We distinguish between mature and young firms. The key difference between mature and young firms is that since the former have a longer track record, investors have a better idea of whether or not they are innovative. For simplicity, we take the extreme view that while the type of a mature firm is known, the type of a young firm is private information. Thus, absent signaling, investors will rely on their priors to make investment decisions concerning young firms. We consider a situation where

$$\frac{1}{2}\alpha V(I) + \frac{1}{2}V(I) < I \tag{1}$$

so that, on the basis of prior information only, young firms are not financed.

The presence of credit constraints gives young innovative firms an incentive to signal their type. We assume that by publishing in academic journals, innovative firms can convey favorable information to investors. There are several reasons why this might be the case. First and foremost, when company scientists publish in referred journals, the academic community *certifies* (through the peer review process) that their research conforms to scientific standards. This provides scientific validation to their claims, for instance, if they argue that the inhibition of a receptor is useful in treating a certain pathology. Second, a substantial publication record conveys favorable information about the ability of the firm's employees. Recent publications, in particular, indicate that company scientists are in touch with the latest developments of their disciplines. Finally, academic publications may be a relatively cheap and fast way to signal competence to outsiders, at least compared to alternatives such as patents.[5]

The structure of the model is as follows. At time 0, innovative firms decide whether or not to publish their research. If they publish, they incur a cost k that may reflect not only the time and resources that firm scientists must put into writing papers, presenting at conferences, etc., but also the risk of expropriation that disclosure typically involves.

At time 1, firms are randomly matched to investors. However, not all investors have the competence or the incentives to examine academic publications.[6] Indeed, evaluating the quality of a firm's R&D requires much more than just counting publications (or patents); at the very least it requires an assessment of the scope, originality and market potential of the firm's research program. To capture these ideas in a simple way, we assume that with probability $\varkappa$ an investor is competent and therefore can, after observing a publication, infer the firm's type. Conversely, with probability $1-\varkappa$ the investor cannot evaluate the publication and retains his prior beliefs. Investor competence is observable after a match and firms have all the bargaining power when negotiating the terms of the contract with financiers.[7] Throughout, we restrict attention to equity financing since this form of finance appears to be very important for young high-technology firms (Roberts, 1991; Moore, 1994; Wright et al., 2006). Furthermore, in the empirical part we will pay special attention to firms that sold some of their equity, either directly or via IPO.

At time 2 parties agree on the terms of the contract and payoffs accrue.

The analysis of this model yields several testable predictions. Consider mature firms. These firms never engage in open science for signaling reasons. In fact, since investors can use track records to tell them apart, if a mature firm is innovative, it always gets financed. Publishing would therefore only reduce its profits from $\alpha V(I) - I$ to $\alpha V(I) - I - k$.

[5] This is especially true for publications in 'hard' sciences (on which this paper focuses), where the time elapsing from submission to publication tends to be short.

[6] This assumption is consistent with Cressy et al. (2007, p. 648)'s claim that specialized private equity firms "possess a deeper knowledge of the competitive environment of acquired companies and their companies' strengths and weaknesses. They are able therefore both to select potentially superior performers and also to provide more effective monitoring and advice once an investment has been made".

[7] Our qualitative results would be the same if firms had only some bargaining power.

The situation is more complicated for young firms. Suppose that at time 0 an innovative firm does not publish. Since (1) holds, it will get

$$\Pi_G^N = \alpha V(0). \tag{2}$$

Now suppose that the firm chooses to publish. Its payoff depends on the type of investor it is matched with. With probability $\varkappa$, the firm is matched with a competent investor who can evaluate its publications. To break even, this investor must demand an equity stake of (at least) s, where s solves

$$s[\alpha V(I) - k] = I. \tag{3}$$

Thus the firm's payoff when the investor is competent is $(1-s)[\alpha V(I) - k] = \alpha V(I) - I - k$. However, with probability $1 - \varkappa$ the firm is matched with an incompetent investor. Since these investors cannot evaluate publications, they never lend money to young ventures, and the firm only gets $\alpha V(0) - k$. By publishing, therefore, an innovative firm gets in expectation

$$\Pi_G^S = \varkappa [\alpha V(I) - I - k] + (1 - \varkappa)[\alpha V(0) - k]. \tag{4}$$

Young, innovative firms publish if $\Pi_G^S > \Pi_G^N$. This condition can be rewritten as

$$\varkappa[\alpha(V(I) - V(0)) - I] > k. \tag{5}$$

Condition (5) implies that young firms will be more likely to publish when α and $\varkappa$ are large and when k is small. Empirically, we will proxy investor competence $\varkappa$ with measures of financial development since, according to Rajan and Zingales (1998, p. 569), "financial development should be related to the variety of intermediaries and markets available, [and] the efficiency with which they perform the evaluation, certification, communication and distribution functions". The key empirical implications of the model can thus be summarized as follows.

H.1 Under the signaling hypothesis, young firms have stronger incentives to publish in academic journals than mature firms.

H.2 Furthermore, the difference in the propensity to publish between young and mature firms should be more pronounced

(i) in more heterogeneous industries (α high) and

(ii) in countries with more developed financial markets ($\varkappa$ high).

In this model young firms have a stronger incentive to publish than mature firms because they face a more severe adverse selection problem. We stress however that the same pattern of results would emerge in a model where asymmetric information is persistent but mature firms are not cash constrained. In that setting, in fact, mature firms could use their internal funds to finance their investments. Again, this would leave only the young firms with the need to signal.

The model predicts that young firms should have the greatest incentives to publish when performance varies substantially across firms. Signaling in fact allows the best firms to differentiate themselves from the worst ones. We should also observe more publications by young firms in highly developed financial markets. Competent investors are in fact more willing to finance young innovative ventures. Moreover, the signaling value of publications is higher when firms can easily find competent investors.[8] The theory does not yield clear-cut predictions on how signaling should be related to product market competition and the need for external funds. Note in fact that while product market competition is likely to increase the threat of expropriation and hence k, it could also affect $V(I) - V(0)$. Aghion et al. (2005), in particular, suggest that the difference $V(I) - V(0)$ should be especially big when competition is fierce (they label this the 'escape-competition' effect). Similarly, the right-hand side of (5) may either increase or decrease with external finance dependence (as parametrized by I), depending on the specific functional form of $V(\cdot)$.

Finally, we should stress that although our discussion focuses on academic publications, the scope of certification is much wider. Hall and Ziedonis (2001), in particular, find that aggressive patenting is sometimes used to attract venture capital. A key difference we envisage when patents instead of publications are used as a signaling device is that in the former case the risk of expropriation is much lower. Indeed, while by publishing firms increase the risk of expropriation, by patenting they can more effectively protect their intellectual assets. In

[8] Signaling may of course not be the only reason why young firms publish more in countries with more developed financial markets. Our model predicts a positive correlation between financial development and the likelihood that young innovative firms are financed (and hence founded). These firms (and especially university spin-offs) could publish not only to attract financiers but also because their founders want to contribute to science ('intrinsic motivation').

terms of the model, this suggests that when patents are used as signals, k could be very low, perhaps negative. Since (5) would then be always verified, we conjecture that

H.3 Young firms may always have very strong incentives to patent, irrespective of industry and country characteristics.

In the empirical analysis we will use firm-level data on patents to explore this possibility.[9]

3. Data

This paper combines data from three main sources: (i) academic publications from the Web of Knowledge database, (ii) patents from the EPO and (iii) financial information from Amadeus. In this section, we explain the methodology for constructing these data and describe our sample.

3.1. Academic Publications

The goal of this paper is to better understand why private firms contribute to the creation and dissemination of scientific knowledge. To this end, we constructed a unique dataset on firm publications. The world's largest source of information on academic publications is the Thomson's ISI Web of Knowledge (WOK), which includes publication records on thousands of international journals in 'hard' sciences (such as natural or physical sciences). Each publication has an address field which contains the authors' affiliation. We match all Amadeus firms by name to the complete ISI database. European research institutions can be incorporated, thus, they appear in Amadeus as potential firms to be matched. To screen out such firms, we follow two steps. First, as for patent matching, we drop Amadeus names that include strings that are associated with research institutions. Second, we manually examine the websites of firms that have a large number of publications but appear as small firms in terms of their sales and number of patents. For these firms, we check whether their primary activity is research. In case the primary activity is research, we exclude them from

[9] It is also important to recognize that the strength of patent protection varies substantially across industries. This would introduce an additional source of variation that is not present in the case of publications. Thus, as H.3 already suggests, firm publications may be better suited to test the signaling hypothesis than patents.

our matched sample. Almost 30 percent of the organizations matched to the WOK database were identified as research or non-for-profit institutions.

Another potential problem with our matching procedure is that we cannot be sure that the research inscribed in a firm publication was actually carried out while the author was working for that firm. For instance, young company scientists might publish research conducted during the course of their studies. However, these kind of problems are unlikely to be particularly severe in our sample because of the very short publication lag in hard sciences. Furthermore, even in those cases firm publications might still convey valuable information about the quality of a firm's workforce.

Finally, to control for publication quality, two sources of information are used. First, we control for the importance of the journal in which the article was published by using the impact factor from the Journal Citations Report. Second, we use information about forward citations at the publication level, where a publication is assumed to be of higher quality if it receives more forward citations.

3.2. Patents

Another instrument that firms might use to signal their ability to perform R&D is the number of patents they hold. To test this conjecture, we constructed a unique dataset of European firm patents by matching all granted patent applications from the EPO to the complete list of Amadeus firms (about 8 million firm names) for the period 1979-2004. More information about this dataset can be found in Belenzon and Berkovitz (2007).

3.3. Accounting

Accounting information is taken from Amadeus - a comprehensive pan-European database by Bureau van Dijk Electronic Publishing (BvDEP), which covers both private and public firms. To ensure we examine firms with substantial economic activity and to harmonize firm coverage across countries, we restrict our sample to include only firms that have at least 10 employees and $1 million. Firms that report only consolidated accounts are excluded. The accounting dataset also provides information on the age of the firm. We refer to the firm age as the number of years elapsed since the date of incorporation. However, the date of incorporation has an important limitation. Legal changes, such as mergers and acquisitions, may in fact affect it. This may cause us, for example, to treat a merger of two mature firms as the formation of a new young company. To mitigate this concern, we follow two steps. First, we manually check the age of the largest publishing firms in our sample using the firm websites and other public sources. We drop firms from the analysis if their age does not correspond to the date of incorporation from Amadeus. Second, we examine all M&A deals during 1997-2004 and manually check the age of firms that participated in these deals and also have at least one academic publication or at least one patent.

4. Descriptive Statistics

The first contribution of this paper is to systematically show that firms publish substantially in academic journals. We matched more than 230 thousand articles in "hard" science journals to European firms in the period 1970-2004. Figure 1 plots the distribution of firm publications across main technology areas. Most firm publications (31 percent) are concentrated in Biology and Chemistry, 22 percent in Engineering and 21 percent in Health and Medicine. The trend is clearly upward. As Figure 2 shows, in the last 20 years the number of firm publications per year has more than quadrupled in most technology areas. For instance, during the period 1990-2004 the number of firm publications per year rose from less than 1000 to more than 4000 in Health and Medicine, and from about 200 to approximately 1000 in Computer Science.

Table A1 provides information on the quality of firm publications. On average, an article receives more than 7 citations, but this figure varies substantially across fields, from a minimum of about 2.5 citations in Computer science to a maximum of 11 citations in Biology and Chemistry. As a comparison, the average of citations received by the non-firm publications (that is, publications we have not matched to Amadeus) is 10.1 (a median of 2). Firm publications also compare somewhat unfavorably with non-firm publications when we look at the impact factor of the journals in which the articles were published. The figures here are 2.14 on average for firm publications and 2.5 for all other publications. The fact that firm publications appear to be of lower quality compared to non-firm publications is not surprising in our view. Firm publications are in fact likely to be directed toward more applied topics. Furthermore, researchers employed by firms may get less exposure (and thus less citations) than their academic counterparts.[10]

[FIGURES 1 AND 2 ABOUT HERE]

Our theory suggests that firms with a short track record may want to use publications to certify and enhance their reputation. We use firm age as a measure of the length of the firm's track record. Figure 3 plots the relationship between firm age and the share of the firms in our sample that publish at least one article out of all innovating firms (where innovating firms include all firms that either patent or publish). We divide firms into quartiles according to their age. The share of firms that publish in the first quartile is substantially higher than the share of firms that publish in the forth quartile (0.32 versus 0.20). This pattern is consistent with the conjecture that publications are especially valuable to firms without an established track record.

Figure 4 examines the relationship between firm age and publication and patent intensities. The pattern of results suggests that young firms have a higher ratio of both publication and patent stocks to sales. Again, this pattern is consistent with the signaling hypothesis.[11]

[FIGURES 3 AND 4 ABOUT HERE]

Table 1 reports summary statistics for firms in our estimation sample. To be included in our estimation sample a firm has to satisfy three conditions: (i) report sales and employment, (ii) have at least one patent or at least one academic publication in the period 1978-2004 and (iii) have at least 10 employees and $1 million in annual sales. About 9 thousand firms have at least one patent or one academic publication between 1978 and 2004. About 3 thousand firms have at least one academic publication, while more than 7 thousand firms have at least

[10] Table A2 examines publications for firms in our estimation sample (see Table 1). We split the publications of these firms according to the median firm age. Publications by mature firms appear to receive more citations compared to publications by young firms. For example, in Biology and Chemistry, an average firm publication receives about 12 citations, while for young firms the average is of approximately 9. Table A3 reports similar statistics when we restrict attention to publications in leading journal only. (Leading journals are defined as those in the highest quartile of the journal impact factor, as indicated by the Journal Citations Report index.) A similar pattern emerges, with publications by mature firms receiving more citations than publications by young firms.

[11] An alternative interpretation of this figure is that there is some non-linearity in the relationship between firm size and innovation. In case the relation between size and innovation is convex we would expect a similar pattern as in figure 4 if young firms are smaller than mature firms. In the econometric estimation we also control for non-linearity in firm size to mitigate this concern.

one patent. Our sample covers a wide distribution of firm size, especially in the lower tail. The median firm in our sample generates about $30 million in annual sales and has 165 employees. 10 percent of the firms in our sample have less than 26 employees and less than $4 million in annual sales.[12] The median firm age is 22 years and the average age is 26. 10 percent of the firms are 6 years of age or younger.

Table 2 reports summary statistics, separately for patenting and publishing firms. Panel A includes only firms that have at least one patent. The average firm has 1,481 employees with a median of 175. On average, these firms have close to 1 patent a year and a stock of patents (assuming a 15 percent annual depreciation rate) of 7 patents. The median age of a patenting firm is 23, with an average age of 29. Panel B of table 2 examines only firms with at least one academic publication. The average publishing firm is larger than the average patenting firm. It has 2,861 employees with a median of 208 and. These firms publish about 1 article a year and have a stock of 4 publications. Publishing firms are slightly younger than patenting firms. The median age of a publishing firm is 19, with an average age of 28.

[**TABLES 1 AND 2 ABOUT HERE**]

5. Econometric Modeling

We use the Negative Binomial model to analyze our publication count data. The key advantage of this model is that it relaxes the Poisson distributional assumption of equality of the conditional variance and mean by allowing for overdispersion.[13] In our baseline specification we estimate a conditional expectation of the form

$$E(P_{it}|X_{it}) = \exp\{\beta_1 Age_{it} + \beta_2 \ln Sales_{it-1} + \mu_c + \varphi_j + \tau_t\}$$

where P_{it} is a count of the number of publications by firm i at time t and X_{it} is a vector of regressors. Age_{it}, defined as the number of year elapsed since that year of incorporation, is the main variable of interest. $Sales_{it-1}$ is used to control for firm size (we use lagged value to mitigate transitory shocks that can affect both the incentive to innovate and sales). μ_c, φ_j and τ_t are complete sets of country, three-digit industry SIC and year dummies, respectively.

[12] As a comparison, Compustat patenting firms have on average $3 billion in annual sales with a median of $500 million (Bloom, Schankerman and Van Reenen, 2005).

[13] See Wooldridge (2002) and Hausman et al. (1984) for discussions of count data models of innovation.

The signaling hypothesis implies that young firms with a shorter track record should be more likely to publish for any given firm size. Thus, we expect $\beta_1 < 0$. We also estimate equivalent specifications where the dependent variable is the number of patents and probit specifications where the dependent variable is an indicator to whether the firm has ever published.

To further explore the signaling hypothesis, we examine how the effect of firm age on publication intensity varies across exogenous industry conditions. We focus mainly on three industry characteristics: the degree of industry heterogeneity in firm performance, dependence on external funds, and the Lerner competition index. To measure industry heterogeneity we follow Acemoglu et. al. (2007) and compute Productivity Growth Dispersion, defined as the difference in the three-year average productivity growth between the 90th and 10th percentiles in a specific industry (we also compute this measure as the difference between the 95th and 5th percentiles and the standard deviation of the industry productivity growth). A high dispersion means that firm performance is affected more by idiosyncratic factors and less by aggregate shocks and systematic industry factors. Thus it should be hard for potential lenders to learn about the quality of an innovating firm by examining aggregate industry information. We compute Productivity Growth Dispersion from the complete set of Amadeus firms for each industry.

To measure dependence on external funds at the industry level we use External Finance Dependence. This is defined as the ratio between capital expenditures minus cash flow from operations and capital expenditures. To compute it, we follow Rajan and Zingales (1998) and rank industries according to their dependence on external funds. These rankings are based on data on US Compustat firms.[14] To be applicable to our European firms, two assumptions are needed. First, technological differences should explain why some industries rely on external funds more than others. Second, these differences should persist across countries. Note also that we face a practical limitation in computing measures of external dependence from Amadeus since we have no information on capital expenditures for European firms.

[14] As discussed by Rajan and Zingales (1998), using data on US firms has important advantages: (i) Since the US market is one of the most advanced capital markets in the world, large publicly-traded firms face the least frictions in accessing finance. This means that the amount of external finance used by these companies is likely to be a pure measure of their demand for external finance. (ii) Disclosure requirements imply that data on external financing are comprehensive. (iii) While using US industry data is rather exogenous to European firms, it is likely that an industry's dependence on external funds in the US is a good measure of its dependence in European countries.

The Lerner index is a commonly used (inverse) proxy for product market competition which is computed as the industry average ratio between profits and revenues.

Our empirical specification becomes

$$\begin{aligned} E(P_{it}|X_{it}) &= \exp\{\beta_1 Age_{it} + \beta_2 Age_{it} \times Industry\ Measure_j \\ &\quad + \beta_3 \ln Sales_{it-1} + \mu_c + \varphi_j + \tau_t\} \end{aligned}$$

where our industry measures are productivity growth dispersion, external finance dependence and the Lerner index. Our main interest is in the coefficient β_2. The most direct implication of the model is that young firms should publish disproportionately more in heterogeneous industries where it is hard for outsiders to evaluate firm quality. Thus we expect β_2 to be negative when age is interacted with productivity growth dispersion.

Finally, we exploit the cross-country variation in our sample by looking at financial development. To measure financial development, we refer to the world-bank indices developed by Beck, Demirgüç-Kunt and Levine (2000, 2007). For each country we examine two measures: stock market and banking system.[15] For the stock market development, we consider the ratio of stock market value traded to GDP; for the banking system, we use the ratio of private credit by deposit money banks and other financial institutions to GDP, where bank deposits are the demand, time, and saving deposits in deposit money banks.[16] Our specification becomes

$$\begin{aligned} E(P_{it}|X_{it}) &= \exp\{\beta_1 Age_{it} + \beta_2 Age_{it} \times FinDev_c \\ &\quad + \beta_3 \ln Sales_{it-1} + \mu_c + \varphi_j + \tau_t\}. \end{aligned}$$

The model predicts that young firms should have stronger incentives to publish in countries with more developed financial markets. Thus, we expect $\beta_2 < 0$.

[15] In addition, following Rajan and Zingales (1998) we also proxy financial development with accounting standards, a measure of the transparency of firms' annual reports.

[16] Table A6 presents measures of financial development for the countries in our sample. Note that although these countries are all members of the European Union and have a relatively high per capita income, they differ significantly in the development of their stock market and banking system. For instance, the ratio of stock market value to GDP is 1.9 in Great Britain and 0.23 in Greece. This is important as it allows for identification.

6. Results

6.1. The Effect of Firm Age

The most basic prediction of our model is that young firms should, ceteris paribus, publish more than mature firms. And if patenting is also used for signaling purposes, the same should be true for patents. Table 3 summarizes the results for the relationship between firm age, publications and patents. Columns 1-6 examine the effect of firm age, measured by years from date of incorporation, on the firm-year number of publications, controlling for firm size (where size is proxied by lagged sales). In columns 1-3 we include the log of firm age, which is significant and negative. This means that as age increases, publications intensity drops. The result is robust to controlling for different proxies of firm size (sales in millions versus log of sales) as well as for nonlinearities. In column 4 firm age is broken down to quartiles, where the first quartile (which includes the youngest firms) is the baseline. The results support the negative relationship between age and publication intensity, since firms in lower age quartiles are more publication intensive than firms in higher age quartiles. For instance, the coefficient on the third quartile of firm age is -0.644 (with a standard error of 0.120), while the coefficient on the forth is -0.911 (with a standard error of 0.117). Columns 5 and 6 examine different sub-samples of firms and give similar results.

In columns 7-10 we conduct the same analysis but now the dependent variable is the firm-year number of patents. The pattern of results also suggests a negative relationship between firm age and patenting intensity. In column 11-13 the relationship between the likelihood of publishing and firm age is considered. The dependent variable is an indicator that receives the value of one if a firm published at least one article and zero otherwise. The sample is cross-sectional for the last year a firm appears in our sample. The estimation results support the pattern in Figure 3 showing that the share of publishing firms is higher in lower quartiles of firm age.

[TABLE 3 ABOUT HERE]

Table 4 examines the robustness of the negative relation between firm age and publications, as found in table 3, when publication quality is taken into account. We use two measures to proxy for the quality of a publication. In columns 1-4 the dependent variable is the firm-year number of citations received. Thus, instead of counting the number of publications a firm has in a given year, we aggregate the number of citations from other publications at the firm-year level. The pattern of results remains the same, with young firms receiving on average more citations than mature firms after controlling for firm size. In columns 5-10 we repeat the analysis separately for publications in low and high impact journals, which yields similar pattern of results.

[TABLE 4 ABOUT HERE]

6.2. Industry Characteristics

Table 5 summarizes the results of Negative Binomial regressions examining the relationship between publication and patent intensities and industry characteristics. Ultimately we are interested in the interactions between these industry characteristics and firm age, as they provide a much cleaner test for the signaling hypothesis. Nevertheless, finding a strong propensity to publish in more heterogeneous industries would clearly lend some support to the model.

In columns 1-2 we examine the relationship between productivity growth dispersion (measuring the industry spread in firm labor productivity growth) and publication intensity. Consistent with our expectations, we find a positive and highly significant coefficient on the dispersion variables. In columns 3-4 we examine the relationship between external finance dependence and publication intensity. The relationship is positive and highly significant, suggesting stronger publication intensity in industries with higher demand for external funds. In column 5 we add the Lerner index of competition (higher values mean less competition) and the industry R&D intensity. Their coefficients are insignificant but the pattern of results for dispersion and external dependence remains the same. In columns 6-10, the dependent variable is the firm-year number of patents. Here the relationship between dispersion and patents is no longer significant, suggesting that patent intensity is not considerably stronger in more heterogeneous industries. Finally, columns 11-15 examine the relationship between industry characteristics and the likelihood of publishing. Similar to columns 1-5, we find a higher likelihood of publishing in more heterogeneous industries and in industries that rely more on external finance.

[TABLE 5 ABOUT HERE]

6.3. Firm Age and Industry Dispersion

Our results so far suggest that firms with a shorter track record and firms that operate in industries where there is greater dispersion are more publication intensive. To strengthen the link between these results and the signaling hypothesis, Table 6 examines whether the interaction between industry dispersion and firm age helps explain publication intensity. According to the theory, young firm should publish disproportionately more in industries where performance varies substantially across firms. Thus, if the signaling hypothesis is correct, we should expect a negative coefficient on the interaction of firm age with industry dispersion. In column 1 we include the interaction between firm age and dispersion. The coefficient on this interaction is negative and significant, supporting the signaling hypothesis. In columns 2-9, we separately estimate the marginal effect of firm age on publication intensity across quartiles of industry dispersion. In the first quartile of dispersion (columns 1-2) the marginal effect of firm age is -0.028 (with a standard error of 0.012). Yet, in the forth quartile (where the heterogeneity in firm performance is the highest), the marginal effect of firm age is -0.192 (with a standard error of 0.032).

Columns 10-18 carry out the same exercise in the patenting equation. We find negative interactions here as well; however, they are small in absolute value compared to the interactions from the publications equation. For example, the marginal effect of firm age in the forth quartile of industry dispersion in the patenting equation is -0.043 (with a standard error of -0.013), while it is -0.192 in the publications equation. This is consistent with our third hypothesis that young firms may always have strong signaling incentives to patent, irrespective of industry conditions.[17]

Table A1 in the Appendix provides additional results and robustness checks. We consider two specifications: one where the dependent variable is the number of publications and another where the dependent variable is a dummy for publishing. Consistent with the signaling hypothesis, the interaction between firm age and industry dispersion is also highly

[17] Of course, an alternative explanation could be that patents are not be well-suited as a signaling device. The importance that private equity firms attach on patents, however, leads us to believe that this is unlikely to be the case.

significant in the probit equation. We find some evidence that young firms publish more in industries that are more dependent on external finance or where competition is less intense, but these results are not statistically significant. This is consistent with the lack of a clear-cut relationship in the model between signaling, the need for external funds, and product market competition. Finally, splitting the sample between articles that were published in high quality journals and those that were published in low quality journals does not change the pattern of results.

[**TABLES 6 ABOUT HERE**]

6.4. Firm Age and Financial Development

Next, we consider how the propensity to publish varies across countries. Our model predicts that young firms should publish disproportionately more in countries where financial markets are highly developed. Financial development should in fact be correlated with the variety and efficiency of financial intermediaries (Rajan and Zingales, 1998) and we would expect competent investors to be more likely to finance innovative start-ups. The incentives to publish should also be enhanced if publications are more thoroughly evaluated (and hence more relevant).

Table 7 summarizes the results for the interaction between country financial development and firm age. Our main measures of financial development are the size of the stock market and the level of private credit over GDP. Consistent with our expectations, we find a negative and significant interaction between these measures of financial development and firm age in the publications equations (columns 1-6 and 10-15). However, when we experiment with another measure of financial development often used in empirical work, accounting standards,[18] the interaction coefficients turn out to be much smaller and generally insignificant (columns 7-9 and 16-18). This may be due to the fact that since accounting standards measure the transparency of firms' annual reports, they may not be a particularly good proxy for the competence of the financial sector.

In unreported regressions, we also consider equivalent specifications where the dependent variable is the firm-year number of patents. As with productivity growth dispersion, we find

[18] This information is from Rajan and Zingales (1998). See also Table A6 in the Appendix.

no significant interactions between measures of financial development and firm age. This lends support to the view that the benefits of patent protection may be substantial and therefore young firms may have very strong incentives to patent, irrespective of country characteristics (hypothesis 3).

A final qualification is that a large fraction of the publications of our sample come from only three countries: the UK, Germany and France (see Table A4). Thus, although we find these results suggestive, more evidence from a larger group of countries is certainly needed before drawing strong conclusions.

[**TABLE 7 ABOUT HERE**]

6.5. Evidence from M&A Deals

This section tests the signaling hypothesis by examining a sub-sample of firms that participated in M&A deals. Since these firms sold some of their equity directly or via IPO, this sample includes only firms that actually raised external finance (by selling equity stakes). The signaling hypothesis suggests that firms with a shorter track record should have strong incentives to publish prior the deal to certify their quality. To test this conjecture we consider the age of a firm in the year the deal was announced (the rumor year). We then test whether younger firms (whose age is calculated at the announcement year) are more likely to have published. We use Zephyr for M&A information during the period 1997-2004 and match this information to our sample of innovating firms. 1,109 innovating firms in the sample sold part of their equity during the estimation period. Out of this number, 482 firms published at least one article prior to the year the deal was announced.

Table 8 summarizes the estimation results. The dependent variable is a dummy that receives the value of 1 for firms that published prior the announcement year and 0 for firms that did not publish. Columns 1-2 examine the marginal effect of firm age on the likelihood of publishing. The results support the signaling hypothesis: firms that have a shorter track record at the year of the deal are more likely to have published at a prior date. Columns 3-8 examine the interaction between firm age and industry characteristics. The signaling hypothesis suggests that young firms should publish disproportionately more in industries with high performance heterogeneity. We indeed find a highly significant negative interaction between firm age and industry heterogeneity. By contrast, the interaction between firm age and the Lerner competition index is insignificant. Consistent with the signaling hypothesis, we also find that young firms tend to publish disproportionately more in countries where financial markets are highly developed. All the results appear to be robust to controlling for publication quality, as measured by the impact factor of the journal in which the article was published.

[TABLE 8 ABOUT HERE]

7. Concluding Remarks

What are the incentives for private firms to engage in open science? Previous work has mainly emphasized the need to monitor and evaluate external research (e.g., Cohen and Levinthal, 1989; Arora and Gambardella, 1990; Cockburn and Henderson, 1998) and, to a lesser extent, the fact that by allowing scientists to publish, companies may be able to attract better researchers or save on their wages (Stern, 2004). These considerations are likely to apply both to mature and young companies. By contrast, young firms might have particularly strong incentives to publish in order to enhance their reputation and signal the quality of their research. As Audretsch and Stephan (1996, p. 646) put it:

> In the early stages of development, biotechnology firms miss no opportunity to signal the abilities of their scientists as well as the science they are undertaking. It is not uncommon for prospectuses to read like proposals to the National Institutes of Health, both in terms of the projects they describe and the accomplishments of the scientists.

Signaling considerations should be especially relevant for high-technology start-ups because the unpredictability of basic research coupled with problems of adverse selection imply that many of these firms will face severe financial constraints. Academic publications can help mitigate these problems by providing scientific validation for the entrepreneur's idea or certification for the firm's human capital. Furthermore in Europe early stage financing is often provided through government schemes such as the University Challenge Funds and SMART in the UK, or direct investment by research institutions as in Germany (Moore and Garnsey, 1992; Wright et al., 2006). We suspect that public institutions may place greater weight on academic credentials than private investors.[19]

The present paper provides evidence consistent with a signaling view of open science. Using a novel and comprehensive database on academic publications, we show that European firms contribute substantially to the advancement of basic scientific knowledge. We also find that, controlling for firm size, young firms publish more than mature firms, and disproportionately so in more heterogeneous industries and in countries where financial markets are highly developed. Our results therefore suggest that financial development, by providing fertile ground for innovative start-ups, may not only spur economic growth, but also promote scientific progress.[20]

These results could be extended in several directions. An interesting finding that emerges from our analysis is that firms that publish are on average larger than those that patent. In ongoing work (Belenzon et al., 2008) we take a closer look at the relationship between firm size and the amount and composition of innovative activity (patents and academic publications). We find that the correlation between firm performance and publications is stronger for large firms than for small firms. By contrast, the correlation between firm performance and patents is stronger for small firms than for large firms. A possible explanation for the former result is that small firms may disproportionately engage in (unproductive) signaling activities to raise funds or to enhance the academic prospects of their founders/key employees.

A second direction for future research would be to supplement our quantitative analysis with evidence of a more qualitative nature. Survey evidence from the US indicates that

[19] Another problem that young firms must face is lack of market legitimacy. New firms must often educate customers and persuade them that the benefits of their products are greater than the risks (Slater, 1993). Shepherd (1999) also finds that venture capitalist's assessments of new venture survival is strongly affected by whether these companies possess this educational capability. An important function of firm publications may be to establish such market legitimacy.

[20] Of course, firm publications may crowd out publications by academic scientists. This would be the case, for instance, if scientists simply chose to use a company affiliation instead of their university affiliation if they have both. However, recent empirical work suggests that working for a private company tends to increase research productivity. Furthermore, the publications of these scientists do not appear to be distorted toward more applied topics. See Looy et al. (2006) and DiMinin and Fabrizio (2008).

young firms are especially likely to patent for reputational reasons (Cohen et al., 2000). It would be important to know if this is also true for academic publications. Furthermore, Murray (2002) argues that the interactions between scientific and technical institutions are unlikely to be fully reflected by bibliometric and patent data. We too found evidence of this in the course of our work. An example is provided by PolyTherics, a London-based biotechnology company founded in 2002 by Professors Brocchini and Shaunak. The company focuses on technology development in the area of biomedical polymers for therapeutic applications; the most advanced of its techniques is site-specific PEGylation, or TheraPEG™. On its website, Polytherics states that "Representative applications of the TheraPEG™ technology have been published in *Nature Chemical Biology*, 2006, p312-323 and a theoretical validation study is due to be published in *Theoretical Chemical Accounts*, 2006".[21] The publication in *Nature Chemical Biology* is also quoted in the company's brochure available at http://www.polytherics.co.uk. These instances appear to be clear examples of signaling. Yet, those articles are not firm publications according to our criteria: Professors Brocchini and Shaunak published these papers using only their academic affiliations. Clearly our operational definition of "firm publication" may just uncover the tip of the iceberg.

Finally, alternatives to the signaling hypothesis could be explored. Absorptive capacity, defensive publications, financial constraints are all plausible reasons why firms may or may not engage in open science, but their relative importance has yet to be assessed. Clearly, much work remains to be done, both theoretically and empirically. We hope that this paper may spur further research (and academic publications) in this exciting area.

[21] This quote is from http://www.polytherics.co.uk/ip.html. The second article, Godwin et al. (2007) was actually published in 2007.

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A. Appendix

A.1. Matching academic publications

The largest database on academic publications is the ISI Web of Knowledge (WoK) by Thomson. This includes millions of records on publications in nearly 9,000 leading academic journals. The data is divided to three main categories based on the publication type: hard sciences, social sciences, and arts and humanities. Because we are interested in capturing investment in scientific research, we focus only on the hard sciences section of WoK. This section includes about 20 million publication records over the period 1970-2004. The address field on each record indicates the affiliation of the authors of the publication. This affiliation is typically either a research institution or a firm. We use the name appearing in this field and match it to the complete list of Amadeus firms. For example, the following is a record in our database. "HIGH-CAPACITY DIGITAL RADIO WITH TRELLIS CODING", BACCETTI B , TAVERNA M , BELLINI S , SALVINI G, EUROPEAN TRANSACTIONS ON TELECOMMUNICATIONS, NOV-DEC 1993. Address: BACCETTI B (reprint author), SIEMENS TELECOMUN SPA, I-20060 CASSINA DE PECCHI, ITALY. The record would be matched to SIEMENS TELECOMUN SPA, which is a firm in Amadeus. We follow the same matching procedure as described above for the EPO and USPTO patent matching. Articles may have more than one author (the median number of authors per article is 2). In this case, the address field would include multiple affiliations. We assign an academic publication to a specific firm if the name of this firm appears at least once in the address field of the article. This procedure means that a single article can be assigned to more than one firm, but a firm cannot be assigned more than once to the same article. For each article, we also extract information on the number of times it was cited, the journal in which it was published, and the year of publication. Information about the importance of journals is taken from the Journal Citations Report index (JCR). The Web Of Science often uses abbreviations. For example, “Chemicals”, “Chemische" (chemical in German) and Chemistry appear as “Chem”. Such standardization is important for name matching, because the name of the same company can appear differently in Amadeus and on the address field of the article (the country origin of each author is also listed for each publication, which ease the translation to English).

Finally, European research institutions can be incorporated, thus, they appear in Amadeus as potential firms to be matched. To screen out such firms, we follow two steps. First, as for patent matching, we drop Amadeus names that include strings that are associated with research institutions (such as, UNIVERSITY, RESEARCH, INSTITUTION, etc.) or government organizations (endings such as, NCR for Italy, CEA for France, etc.). Second, we manually examine the websites of firms that have a large number of publications but appear as small firms in terms of their sales and number of patents. For these firms, we check whether their primary activity is research. In case the primary activity is research, we exclude them from our matched sample. At the end of this procedure we are left with 234,864 publications that are matched to 21,052 Amadeus firms. Because our aim is to examine the effect of publications on firms performance, we match to the publishing firms accounting information. Firms that never report accounting information are dropped from our sample. After dropping firms with no financial information, we are left with 163,833 firm publications between 1970 and 2004. Over the estimation period, 1995-2004, our sample of firms publish 87,671 articles. Figure B7 plots the total number of firm publications over time. Starting at 1990 there has been a sharp increase in the number of firm publications, especially Biology and Chemistry, Health and Medicine and Engineering. A similar pattern holds when we include only firm publications in leading journal (journals with above median impact factor).

A.2. Matching patent data: the European Patent Office (EPO)

The matching between EPO patent applicants and Amadeus firms has been a collaborative project with the Institute for Fiscal Studies (IFS) and the Centre for Economic Performance (CEP).[22] This section is a brief summary of the matching procedure described in the CEP/IFS AmaPat document and is included here for completeness. See also Belenzon and Berkovitz (2007).

Our main information source on patents is the April 2004 publication of the PATSTAT database, which is the standard source for European patent data. This database contains all bibliographic data (including citations) on all European patent applications and granted patents, from the beginning of the EPO system in 1979 to 2004.

We match the name of each EPO applicant listed on the patent document to the full name of a firm listed in Amadeus (about 8 million names). Since we are interested only in matching patent applicants to firms, we exclude applicant names that fall into the following categories: government agencies, universities, and individuals. We identify government agencies and universities by searching for a set of identifying strings in their name. We identify individuals as patents where the assignee and the inventor name strings are identical.

The matching procedure follows two main steps. (i) Standardizing names of patent applicants. This involves replacing commonly used strings which symbolize the same thing, for example "Ltd." and "Limited" in the UK.[23] We remove spaces between characters and transform all letters to capital letters. As an example, the name "British Nuclear Fuels Public Limited Company" becomes "BRITISHNUCLEARFUELSPLC". (ii) Name matching: match the standard names of the patent applicants with Amadeus firms. If there is no match, then try to match to the old firm name available in Amadeus. We need to confront a number of issues. First, in any given year, the Amadeus database excludes the names of firms that have not filed financial reports for four consecutive years (e.g. M&A, default). We deal with this issue in several ways. First, we use information from historical versions of the Amadeus database (1995-2003) on names and name changes. Second, even though Amadeus contains a unique firm identifier (BVD ID number), there are cases in which firms with identical names have different BVD numbers. In these cases, we use other variables for identification, for example: address (ZIP code), Date of incorporation (whether consistent with the patent application date), and more. Finally, we manually match most of the remaining corporate patents to the list of Amadeus firms.

[22] We extend our gratitude to the tremendous work done by Rachel Griffith and the IFS team, especially Gareth Macartney in developing and implementing the patent matching. More information about the matching is available at: "AmaPat: Accounting, Ownership and Patents for European Firms" (CEP/IFS AmaPat document).

[23] The complete list of strings is available in the CEP/IFS AmaPat document.

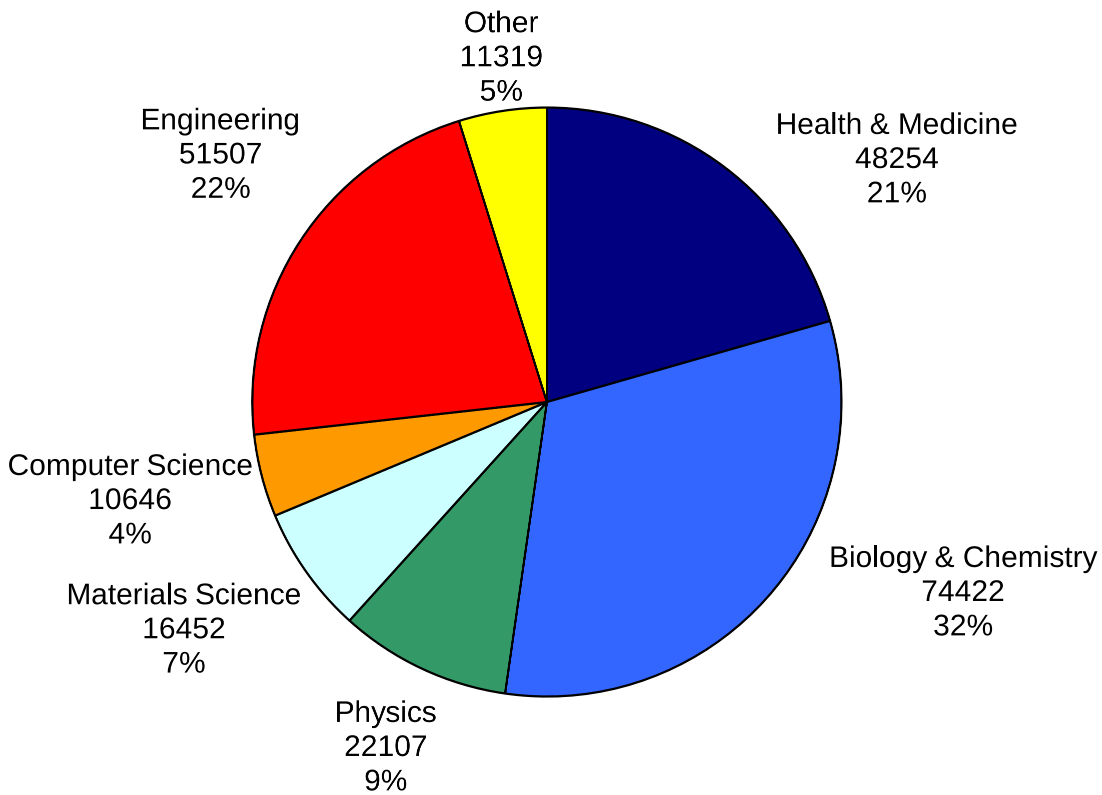
A.3. Accounting database

The accounting information is taken from Amadeus. The database contains financial information on about 8 million firms from 34 countries, including all the European Union countries and Eastern Europe. The accounts of each firm are followed for up to ten years. The information source for Amadeus is about 50 country vendors (generally the office of register of Companies). The main advantage of Amadeus over other data sources is its coverage of small and medium size firms.

The accounting database includes items from the balance sheet (22 items) and income statement (22 items). No information is available from the changes in cash flow report (i.e., investment data is not available). The accounting data is harmonized by BvD to enhance comparison across countries. This comparison becomes easier over time due to the improvement in the European Union harmonization is accounting standards. In addition to accounting data items, Amadeus provides a description of firms including their product market activity. The main descriptive items are legal form (public versus private), date of incorporation, types of accounts (consolidated versus unconsolidated), country, US SIC and NAIC for the product market activity of the firm (primary and non-primary). The industry location information includes up to eight different six-digit NAIC codes per firm (note that the sales of the firm are not broken-up across the different product markets).

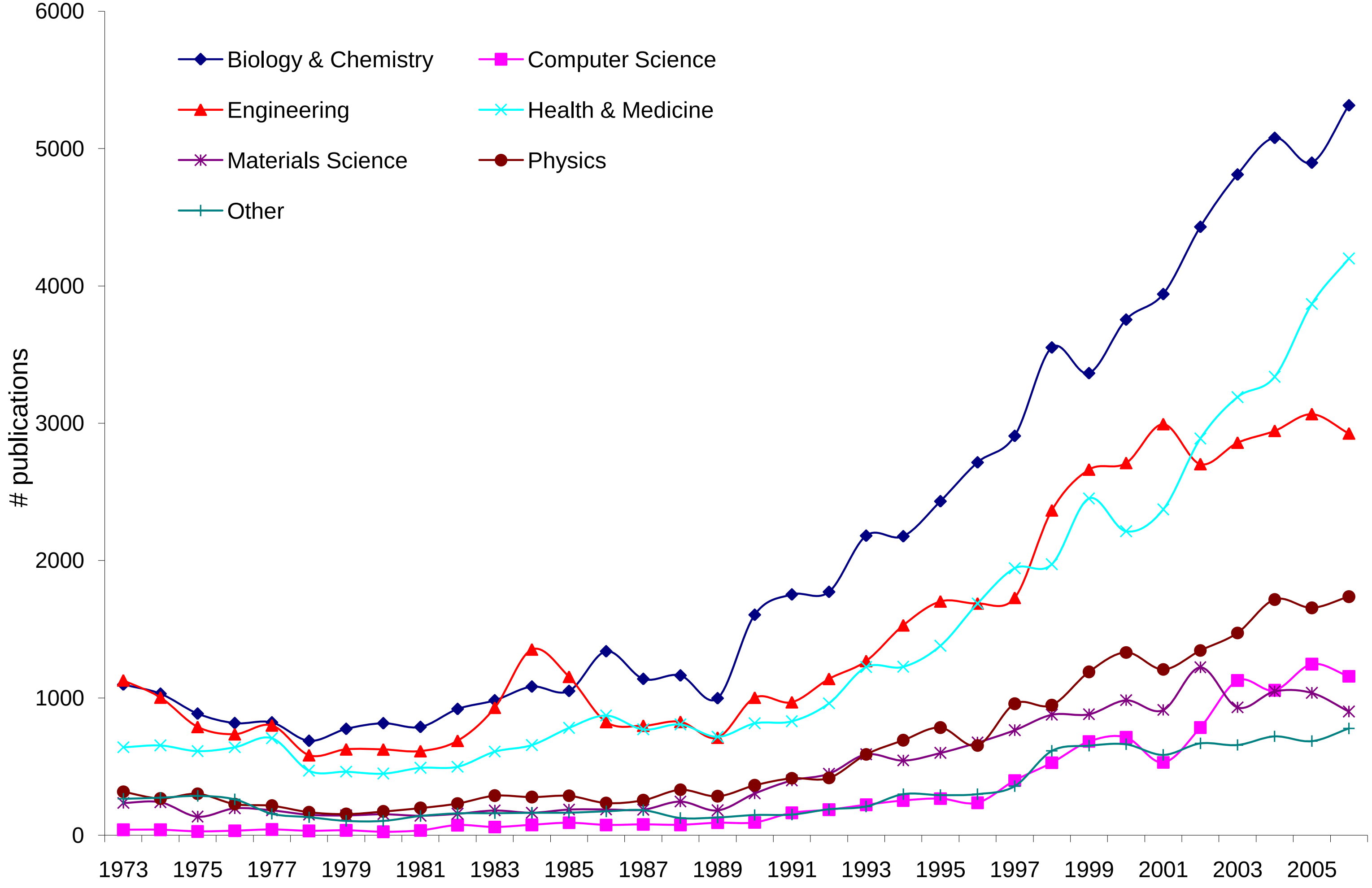
An important feature of the data is the criteria for dropping firms from the sample over time. As long as a firm continues to file its financial statements, it continues to appear in Amadeus. In case a firm becomes inactive, it stops filing its financial statement (alternatively, a firm can be late in filing its financial statement). This firm will be kept in the sample for four extra years since the last year financial statements were reported (thus, in the fifth year the firm will be removed from the sample). For example, a firm that becomes inactive and stops filing its reports in 1995 (i.e., 1994 is the last year when a financial statement was reported) will remain in the database until 1998 (including) and in 1999, it will be dropped from the sample (all observations of the specific firm will be taken out from the Amadeus database in the 1999 update). In order to mitigate the problem of losing dead firms, we purchased old Amadeus disks that allow tracking firms that exit the sample in previous years. For example, the firm that exits in 1995 will appear in the 1998 Amadeus disk, but not in the 1999 disk. By using both 1998 and 1999 disks, we mitigate the selection bias of dropping inactive firms after 4 years of missing data.

FIGURE 1: FIRM PUBLICATIONS ACROSS MAIN TECHNOLOGY AREAS (234,707 ARTICLES BETWEEN 1970 AND 2005)



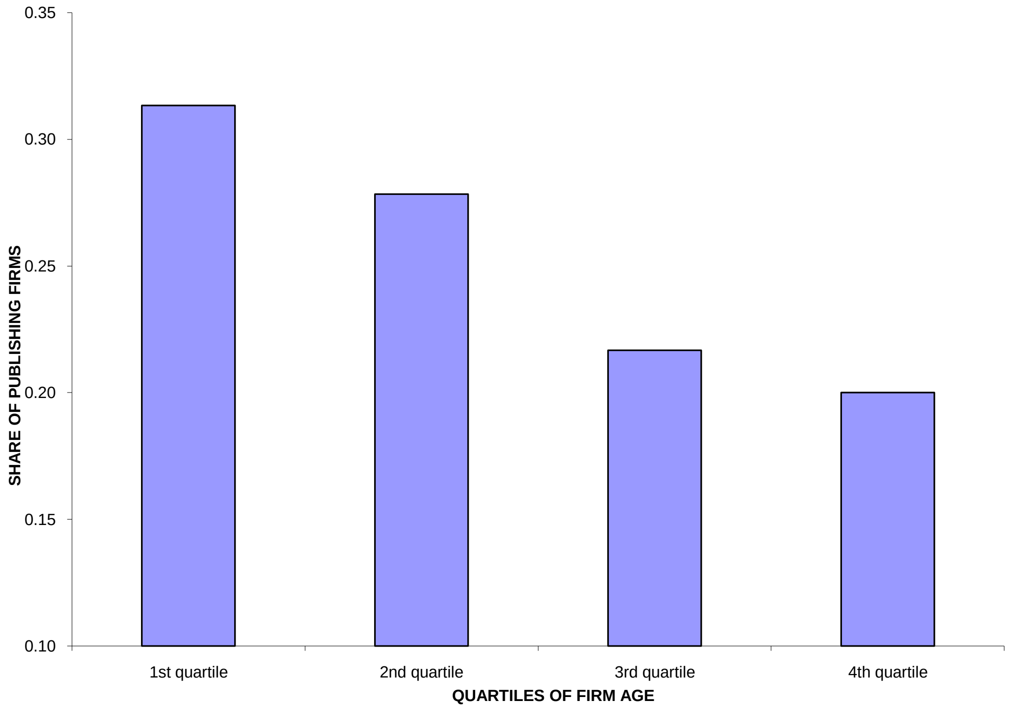
Notes: This figure plots the distribution of firm publications across main technology areas. We include all publication that were matched to about 8m European firms from Amadeus over the period 1970-2005. The academic publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database.

FIGURE 2: FIRM PUBLICATIONS OVER TIME AND ACROSS MAIN TECHNOLOGY AREAS



Notes: This figure plots the distribution of firm publications over time and across main technology areas. We include all publication that were matched to about 8m European firms from Amadeus over the period 1970-2005. The academic publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database.

FIGURE 3: SHARE OF PUBLISHING FIRMS ACROSS FIRM AGE QUARTILES



Notes: This figure plots the share of publishing firms across firm age quartiles. A firm is assumed not to publish if there is no single match between the name of the firms and the ISI Web of Science in the period 1970-2005. Firm age is years from date of incorporation, computed at the last year where financials are reported. The sample includes all Amadeus firms with at least one patent or one academic publication in "hard" science journals between 1978 and 2004. Firms in our sample are required to have more than 10 employees and $1 in annual sales in the last year they report accounts.

FIGURE 4A: PUBLICATIONS INTENSITY AND FIRM AGE

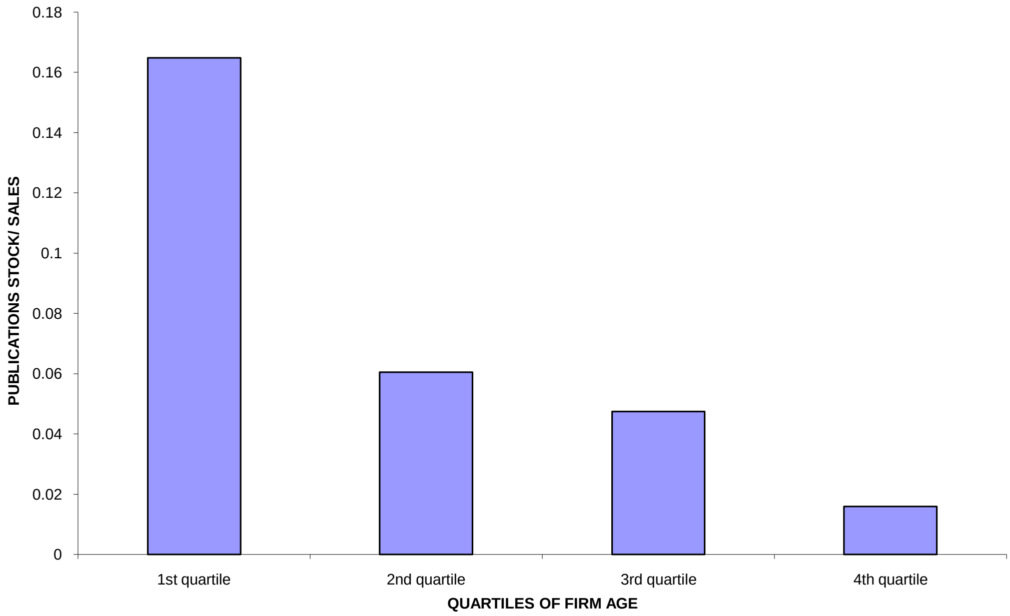
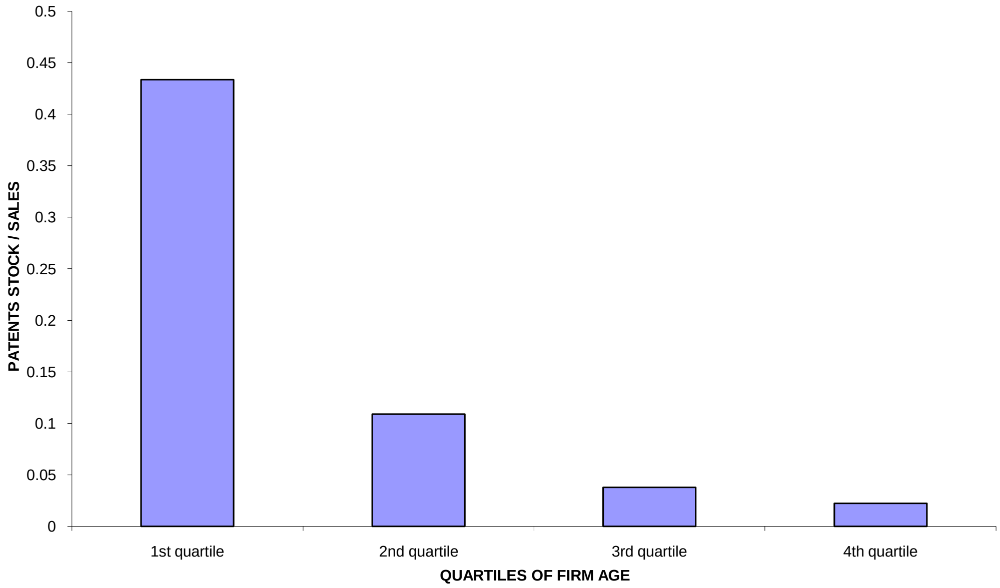


FIGURE 4B: PATENTS INTENSITY AND FIRM AGE



Notes: Figure 4A plots publications intensity (defined as the ratio between a firm's publications stock and its sales) across quartiles of firm age. Figure 4B provides the same information for patents intensity. Firm age is years from date of incorporation, computed at the last year where financials are reported. Sales are in millions of US dollars. The sample includes all Amadeus firms with at least one patent or one academic publication in "hard" science journals between 1978 and 2004. Firms in our sample are required to have more than 10 employees and $1 in annual sales in the last year they

TABLE 1-

SUMMARY STATISTICS FOR MAIN FIRM CHARACTERISTICS (FIRM-YEAR)

Variable	# firms	# Obs	Mean	Std. Dev.	Distribution 10st	50th	90th
# of publications	2,835	12,953	1.1	5.6	0	0	2
# of patents	7,374	33,712	0.8	5.8	0	0	1
Publications stock	2,835	12,953	4.3	18.7	0	0.9	8.0
Patents stock	7,374	33,712	7.1	42.0	0.1	0.9	12.3
Sales (`000)	9,239	41,754	403,913	3,660,317	4,042	29,025	393,230
Employess	9,239	41,754	1,430	10,363	26	165	1,658
Age	9,239	41,754	29	23	6	22	64
Capital (`000)	8,238	37,993	312,862	3,933,511	431	6,632	162,871
Cash flow (`000)	8,021	36,591	48,085	543,923	-727	1,685	34,588

Notes: This table provides summary statistics for firms in our estimation sample over the period 1995-2004. The sample includes all Amadeus firms with at least one patent or one academic publication in "hard" science journals between 1978 and 2004. Academic publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database. Patents are constructed by matching the name of all Amadeus firms to all EPO patent records for the period 1978-2004. Cash is defined as net income plus depreciation. Capital is defined as fixed-assets. Age is the number of years since the date of incorporation. Patents and publication stocks are computed using the perpetual inventory method using a depreciation rate of 15 percent.

TABLE 2-

COMPARISON OF KEY VARIABLES: PATENTING FIRMS VERSUS PUBLISHING FIRMS

PANEL A: PATENTING

Variable	# firms	# Obs	Mean	Std. Dev.	Distribution		
					10st	50th	90th
# of patents	7,374	33,712	0.8	5.8	0	0	1
Patents stock	7,374	33,712	7.1	42.0	0.1	0.9	12.3
Sales (`000)	7,374	33,712	389,418	3,290,521	4,269	29,611	390,279
Employess	7,374	33,712	1,481	10,871	28	175	1,746
Age	7,374	33,712	29	23	6	23	65
Capital (`000)	6,405	30,067	313,297	4,106,974	554	7,335	162,320
Cash flow (`000)	6,263	29,060	45,623	512,340	-780	1,762	33,856

PANEL B: PUBLISHING

Variable	# firms	# Obs	Mean	Std. Dev.	Distribution		
					10st	50th	90th
# of publications	2,835	12,953	1.1	5.6	0	0	2
Publications Stock	2,835	12,953	4.3	18.7	0	0.9	7.9
Sales (`000)	2,835	12,953	891,975	6,251,996	4,046	43,661	908,252
Employess	2,835	12,953	2,865	17,359	26	208	3,008
Age	2,835	12,953	28	23	5	19	65
Capital (`000)	2,698	12,471	612,573	4,669,980	305	10,462	442,950
Cash flow (`000)	2,593	11,827	103,710	810,476	-891	2,535	83,331

Notes: This table provides summary statistics for firms in our estimation sample over the period 1995-2004. The sample includes all Amadeus firms with at least one patent or one academic publication in "hard" science journals between 1978 and 2004. Panel A is for firms that have at least one patent between 1978 and 2004 and panel B is for firms that have at least one publication over the same period. Patents are constructed by matching the name of all Amadeus firms to all EPO records for the period 1978-2004. Academic publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database. Cash is defined as net income plus depreciation. Capital is defined as fixed-assets. Age is the number of years since the date of incorporation. Patents and publication stocks are computed using the perpetual inventory method using a depreciation rate of 15 percent.

TABLE 3-

THE RELATIONSHIP BETWEEN PUBLICATIONS, PATENTS AND FIRM AGE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Dependent variable:	# of publications (Negative Binomial)						# of patents (Negative Binomial)				Dummy for publications (Probit)		
Firms:	All	All	All	All	Age>1st quartile	Only publishing	All	All	Age>1st quartile	Only patenting	All	All	Age>1st quartile
log(Firm Age)	-0.273***	-0.276***	-0.410***				-0.122***				-0.063***		
	(0.050)	(0.050)	(0.045)				(0.030)				(0.019)		
Firm Age quartiles:													
Dummy for 2nd quartile				-0.478***		-0.311***		-0.182***		-0.183***		-0.066	
				(0.096)		(0.086)		(0.068)		(0.063)		(0.042)	
Dummy for 3rd quartile				-0.644***	-0.226**	-0.458***		-0.231***	-0.084	-0.207***		-0.158***	-0.097**
				(0.120)	(0.117)	(0.110)		(0.072)	(0.071)	(0.069)		(0.045)	(0.045)
Dummy for 4th quartile				-0.911***	-0.491***	-0.681***		-0.289***	-0.219***	-0.308***		-0.118**	-0.051
				(0.117)	(0.115)	(0.124)		(0.075)	(0.075)	(0.072)		(0.047)	(0.048)
$\log(\text{Sales})_{t-1}$			0.476***	0.474***	0.510***	0.346***	0.545***	0.544***	0.590***	0.559***	0.476***	0.118***	0.127***
			(0.027)	(0.025)	(0.032)	(0.022)	(0.019)	(0.019)	(0.021)	(0.018)	(0.027)	(0.010)	(0.013)
Sales_{t-1} ($\times 10^6$)	0.256***	0.343***											
	(0.062)	(0.057)											
Sales^2_{t-1} ($\times 10^6$)		-0.014***											
		(0.002)											
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-11,028.7	-10,995.3	-11,072.5	-16,492.3	-10,406.1	-13,228.7	-22,975.7	-23,080.1	-15,937.0	-21,921.5	-4,387.2	-4,395.1	-3,120.7
# Firms	9,239	9,239	9,239	9,239	6,667	2,816	9,239	9,239	6,667	7,374	9,239	9,239	6,667
# Observations	41,754	41,754	41,754	41,754	29,518	12,888	41,754	41,754	29,518	33,712	9,239	9,239	6,667

Notes: This table reports the results of Negative Binomial regressions examining the relationship between publications, patents and firm age. The sample includes all Amadeus firms with at least one patent or one academic publication in "hard" science journals between 1978 and 2004 that have at least 10 employees and $1 million in sales. Age is calculated from the date of incorporation. The sample includes firms that have at least one patent or one academic publication in "hard" science journals between 1978 and 2004, have at least 10 employees and at least $1 million in annual sales. The sample in columns 11-13 is cross-sectional for the last year financials are available for each firm. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 4-

PUBLICATIONS AND FIRM AGE: CONTROLLING FOR PUBLICATION QUALITY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	# of citations received (Negative Binomial)				# of publications (Negative Binomial)					
Journal Impact Factor	All				Below median			Above median		
Firms:	All	All	Age>1st quartile	Only publishing	All	All	Age>1st quartile	All	All	Age>1st quartile
log(Firm Age)	-0.596***				-0.417***			-0.355***		
	(0.032)				(0.050)			(0.056)		
Firm Age quartiles:										
Dummy for 2nd quartile		-0.620***		-0.528***		-0.507***			-0.496***	
		(0.133)		(0.116)		(0.107)			(0.127)	
Dummy for 3rd quartile		-0.902***	-0.460***	-0.701***		-0.658***	-0.184		-0.562***	-0.162
		(0.149)	(0.153)	(0.148)		(0.128)	(0.120)		(0.157)	(0.154)
Dummy for 4th quartile		-1.350***	-0.887***	-1.089***		-0.974***	-0.480***		-0.771***	-0.375**
		(0.147)	(0.173)	(0.158)		(0.125)	(0.120)		(0.159)	(0.161)
log(Sales)$_{t-1}$	0.519***	0.516***	0.590***	0.362***	0.494***	0.494***	0.515***	0.449***	0.444***	0.493***
	(0.032)	(0.031)	(0.041)	(0.028)	(0.027)	(0.027)	(0.031)	(0.033)	(0.033)	(0.043)
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-22,199.3	-22,256.6	-13,959.9	-18,770.4	-10,762.0	-10,796.2	-6,902.4	-8,859	-8,888.9	-5,527.3
# Firms	9,239	9,239	6,667	2,816	8,432	8,432	6,316	7,988	7,988	5,966
# Observations	41,754	41,754	29,518	12,888	38,071	38,071	27,718	35,775	35,775	26,023

Notes: This table reports the results of Negative Binomial regressions that examine the relationship between publication quality and firm age, controlling for the quality of publications. The sample includes firms that have at least one patent or one academic publication in "hard" science journals between 1978 and 2004, have at least 10 employees and at least $1 million in annual sales. Age is calculated from the date of incorporation. Journal Impact Factor is a measure of the importance of a journal and is included in the ISI database. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 5-

THE RELATIONSHIP BETWEEN PUBLICATIONS AND PATENTS AND INDUSTRY CHARACTERISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dependent variable:	# of publications (Negative Binomial)					# of patents (Negative Binomial)					Dummy for publishing (Probit)				
Productivity Growth Dispersion (90-10)	1.931***			1.231***	1.335***	0.097			0.027	0.018	0.437***			0.439***	0.432***
	(0.337)			(0.282)	(0.287)	(0.150)			(0.152)	(0.154)	(0.058)			(0.053)	(0.052)
Productivity Growth Dispersion (95-5)		1.298***					0.092					0.299***			
		(0.161)					(0.088)					(0.037)			
External Finance Dependence			0.637***	0.605***	0.523***			0.248***	0.247***	0.265***			0.270***	0.273***	0.299***
			(0.064)	(0.064)	(0.101)			(0.037)	(0.037)	(0.061)			(0.017)	(0.017)	(0.022)
Lerner Competition Index					0.488					-2.017*					2.045***
					(1.335)					(1.129)					(0.558)
Industry mean of R&D / Sales					0.032					-0.003					-0.007
					(0.029)					(0.020)					(0.007)
log(Firm Age)	-0.418***	-0.417***	-0.433***	-0.389***	-0.390***	-0.149***	-0.147***	-0.129***	-0.128***	-0.128***	-0.142***	-0.138***	-0.142***	-0.117	-0.115***
	(0.067)	(0.066)	(0.072)	(0.076)	(0.075)	(0.035)	(0.035)	(0.034)	(0.034)	(0.034)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)
$\log(\text{Sales})_{t-1}$	0.453***	0.469***	0.396***	0.412***	0.410***	0.517***	0.517***	0.515***	0.513***	0.516***	0.115***	0.115***	0.117***	0.122***	0.124***
	(0.040)	(0.039)	(0.030)	(0.031)	(0.031)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Three-digit SIC dummies	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-16,992.0	-16,934.7	-16,871.7	-16,639.6	-16,634.1	-23,687.5	-23,685.9	-23,617.7	-23,589.4	-23,584.8	-5,068.4	-5,051.9	-5,059.4	-4,927.3	-4,917.5
# Firms	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239	9,239
# Observations	41,754	41,754	41,754	41,754	41,754	41,754	41,754	41,754	41,754	41,754	9,239	9,239	9,239	9,239	9,239

Notes: This table examines the relationship between industry consitions, patenting and publications intensity. Productivity Growth Dispersion (90-10) is the difference in annual growth rate in productivity between the 90th and 10th deciles within an industry and is based on Acemoglu et al. (2007). External Finance Dependence is defined as the ratio between capital expenditures minus cash flow from operations and capital expenditures and is based on Rajan and Zingales (1998). The Lerner competition index is the industry average ratio between profits and sales. The sample includes all Amadeus firms with at least one patent or one academic publication in "hard" science journals between 1978 and 2004 and have at least 10 employees and $1 million in annual sales. The sample in columns 11-15 is cross-sectional for the last year financials are available for each firm. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 6-

FIRM AGE AND PRODUCTIVITY GROWTH DISPERSION (PGD). NEGATIVE BINOMIAL ESTIMATION

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent variable:	# of publications (marginal effects)									# of patents (marginal effects)								
PGD quartile:	All	1st quartile		2nd quartile		3rd quartile		4th quartile		*All*	1st quartile		2nd quartile		3rd quartile		4th quartile	
PGD × log(Firm Age)	-0.233**									-0.035								
	(0.107)									(0.066)								
log(Firm Age)	-0.326***	-0.028**		-0.017***		-0.053***		-0.192***		-0.012	-0.016**		-0.013		-0.023**		-0.043***	
	(0.064)	(0.012)		(0.021)		(0.014)		(0.032)		(0.010)	(0.008)		(0.011)		(0.009)		(0.013)	
Firm Age quartiles:																		
Dummy for 2nd quartile			-0.040**		-0.111***		-0.064***		-0.197***			-0.030**		-0.030		-0.015		-0.060**
			(0.019)		(0.033)		(0.022)		(0.043)			(0.014)		(0.021)		(0.020)		(0.027)
Dummy for 3rd quartile			-0.041*		-0.119***		-0.093***		-0.270***			-0.028*		-0.032		-0.032		-0.071***
			(0.024)		(0.040)		(0.021)		(0.051)			(0.017)		(0.023)		(0.020)		(0.027)
Dummy for 4th quartile			-0.060***		-0.121***		-0.089***		-0.322***			-0.039**		-0.030		-0.046**		-0.091***
			(0.023)		(0.044)		(0.021)		(0.049)			(0.018)		(0.025)		(0.021)		(0.024)
$\log(\text{Sales})_{t-1}$	0.479***	0.035***	0.036***	0.134***	0.128***	0.057***	0.055***	0.078***	0.079***	0.083***	0.082***	0.082***	0.113***	0.114***	0.067	0.068***	0.069***	0.069***
	(0.026)	(0.006)	(0.006)	(0.022)	(0.020)	(0.006)	(0.006)	(0.014)	(0.013)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)	(0.005)	(0.005)	(0.009)	(0.009)
Three-digit SIC dummies	Yes	No	No	No	No	No	No	No	No	Yes	No	No	No	No	No	No	No	No
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-15,840.8	-2,492.0	-2,493.9	-4,675.5	-4,693.9	-3,547.1	-3,558.9	-5,955.4	-5,960.5	-23,682.6	-5,874.4	-5,895.6	-6,510.4	-6,553.7	-5,629.2	-5,648.5	-5,454.7	-5,473.2
# Firms	9,239	2,208	2,208	2,137	2,140	2,143	2,143	2,350	2,350	9,239	2,208	2,208	2,137	2,140	2,143	2,143	2,350	2,350
# Observations	41,754	10,348	10,348	9,703	9,703	9,782	9,782	11,921	11,921	41,754	10,348	10,348	9,703	9,703	9,782	9,782	11,921	11,921

Notes: This table examines the relationship between industry firm heterogeneity, patenting and publications intensity and firm age. Productivity Growth Dispersion is the difference in annual growth rate in productivity between the 90th and 10th deciles within an industry and is based on Acemoglu et al. (2007). The sample includes firms that have at least one patent or one academic publication in "hard" science journals between 1978 and 2004, have at least 10 employees and at least $1 million in annual sales. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 7-

THE RELATIONSHIP BETWEEN FIRM AGE AND A COUNTRY'S FINANCIAL DEVELOPMENT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent variable:	# of publications (Negative Binomial)									Dummy for publishing (Probit)								
Financial Development:	Stock Market Value Traded / GDP			Private Credit / GDP			Accounting standards			Stock Market Value Traded / GDP			Private Credit / GDP			Accounting standards		
Journal Impact factor:	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median
Financial Development × log(Firm Age)	-0.195**	-0.247***	-0.153	-0.364***	-0.349**	-0.374**	-0.049	-0.107**	-0.008	-0.091**	-0.095**	-0.105**	-0.168***	-0.208***	-0.117	-0.039*	-0.048**	-0.031
	(0.083)	(0.087)	(0.112)	(0.143)	(0.155)	(0.189)	(0.049)	(0.054)	(0.063)	(0.037)	(0.040)	(0.046)	(0.064)	(0.068)	(0.078)	(0.023)	(0.024)	(0.028)
log(Firm Age)	-0.204**	-0.159	-0.193	0.031	0.004	0.102	-0.065	0.342	-0.297	0.030	0.080*	0.010	0.140*	0.234***	0.043	0.210	0.320*	0.122
	(0.098)	(0.105)	(0.123)	(0.175)	(0.191)	(0.229)	(0.355)	(0.393)	(0.448)	(0.044)	(0.047)	(0.053)	(0.080)	(0.086)	(0.096)	(0.164)	(0.174)	(0.120)
log(Sales)$_{t-1}$	0.479***	0.495***	0.451***	0.479***	0.492***	0.450***	0.478***	0.495***	0.450***	0.120***	0.136***	0.129***	0.119***	0.135***	0.129***	0.120***	0.136***	0.129***
	(0.026)	(0.027)	(0.033)	(0.026)	(0.027)	(0.033)	(0.026)	(0.027)	(0.033)	(0.010)	(0.011)	(0.013)	(0.010)	(0.011)	(0.013)	(0.010)	(0.011)	(0.013)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-16,038.4	-10,782.3	-8,881.6	-16,037.9	-10,785.2	-8,879.8	-16,043.7	-10,785.6	-8,883.9	-4,386.7	-3,881.5	-2,778.8	-4,386.3	-3,879.9	-2,780.4	-4,388.2	-3,882.6	-2,780.9
# Firms	9,239	8,496	8,204	9,239	8,496	8,204	9,239	8,496	8,204	9,239	8,496	8,204	9,239	8,496	8,204	9,239	8,496	8,204
# Observations	41,754	39,039	36,534	41,754	39,039	36,534	41,754	39,039	36,534	9,239	8,496	36,534	9,239	8,496	8,204	9,239	8,496	8,204

Notes: This table examines the relationship between publications and country's financial development across firm age. Firm age is years from date of incorporation. The measures of financial development are for 2005 and are based on Beck et al. (2000, 2007). Stock Market Value Traded is total shares traded on the stock market exchange. Private Credit is the ratio of private credit by deposit money banks and other financial institutions. Accounting standards is from Rajan and Zingales (2000). The sample includes firms that have at least one patent or one academic publication in "hard" science journals between 1978 and 2004, have at least 10 employees and at least $1 million in annual sales. The sample in columns 10-18 is cross-sectional for the last year financials are available for each firm. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 8-

EVIDENCE FROM MERGERS AND ACQUISITIONS: FIRM AGE, INDUSTRY CHARACTERISTICS AND COUNTRY'S FINANCIAL DEVELOPMENT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Industry / Country measure:	-		Productivity Growth Dispersion (90-10)			Lerner index (Profits/Sales)			Stock Market Value Traded / GDP			Private Credit / GDP			Accounting standards		
Journal Impact factor:	All		All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median
Industry/Country measure × log(Firm Age)			-0.598***	-0.571**	-0.574**	1.991	3.409**	2.074	-0.372***	-0.503***	-0.275***	-0.611***	-0.646***	-0.390**	-0.204***	-0.258***	-0.172**
			(0.216)	(0.227)	(0.230)	(1.294)	(1.686)	(1.404)	(0.092)	(0.097)	(0.106)	(0.152)	(0.169)	(0.171)	(0.065)	(0.068)	(0.075)
log(Firm Age)	-0.061***		0.167*	0.272***	0.104	-0.219**	-0.189*	-0.287***	0.256***	0.515***	0.094	0.622***	0.784***	0.230	1.316***	1.812***	1.024**
	(0.016)		(0.095)	(0.099)	(0.103)	(0.097)	(0.117)	(0.111)	(0.099)	(0.106)	(0.110)	(0.190)	(0.210)	(0.212)	(0.445)	(0.469)	(0.512)
Firm Age quartiles:																	
Dummy for 2nd quartile		-0.016															
		(0.054)															
Dummy for 3rd quartile		-0.137***															
		(0.049)															
Dummy for 4th quartile		-0.180***															
		(0.047)															
$\log(\text{Sales})_{t-1}$	0.044***	0.045***	0.126***	0.165***	0.166***	0.124***	0.160***	0.165***	0.128***	0.167***	0.166***	0.133***	0.169***	0.169***	0.127***	0.163***	0.167***
	(0.001)	(0.007)	(0.025)	(0.028)	(0.031)	(0.025)	(0.027)	(0.031)	(0.025)	(0.027)	(0.031)	(0.025)	(0.027)	(0.031)	(0.025)	(0.027)	(0.031)
Country dummies	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-722.2	-718.3	-541.9	-489.2	-387.9	-548.7	-494.2	-394.5	-542.2	-485.1	-392.4	-542.1	-489.4	-393.1	-544.8	-489.8	-392.9
# Firms	1,109	1,109	1,123	1,072	1,011	1,123	1,072	1,011	1,123	1,072	1,011	1,123	1,072	1,011	1,123	1,072	1,011

Notes: Notes: This table examine the relationship between firm age and publications for a sample of Amadeus firms that were aquired in M&A deals during 1999-2004 and have at least one patent or one academic publication in "hard" science journals between 1978 and 2004, have at least 10 employees and at least $1 million in annual sales. The dependent variable is a dummy of whether the aquired firm has ever published. Productivity Growth Dispersion is the difference in annual growth rate in productivity between the 90th and 10th deciles within an industry and are based on Aghion et al., 2005. The measures of financial development are for 2005 and are based on Beck et al. (2000, 2007). Stock Market Value Traded is total shares traded on the stock market exchange. Private Credit is the ratio of private credit by deposit money banks and other financial institutions. Accounting standards is from Rajan and Zingales (2000). All regressions include complete sets of year (10) and country (12) dummies. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE A1-

THE RELATIONSHIP BETWEEN FIRM AGE AND INDUSTRY CHARACTERISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent variable:	# of publications (Negative Binomial)									Dummy for publishing (Probit)								
Industry measure:	Productivity Growth Dispersion (90-10)			External Finance Dependence			Lerner index (Profits/Sales)			Productivity Growth Dispersion (90-10)			External Finance Dependence			Lerner index (Profits/Sales)		
Journal Impact factor:	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median	All	Below median	Above median
Financial Development × log(Firm Age)	-0.233**	-0.207*	-0.491***	0.058	-0.040	0.104**	1.074	2.426**	0.104**	-0.139**	-0.131**	-0.132**	-0.011	-0.027	0.023	0.283	0.964*	0.391
	(0.107)	(0.126)	(0.182)	(0.043)	(0.044)	(0.041)	(1.036)	(1.059)	(0.041)	(0.058)	(0.059)	(0.065)	(0.019)	(0.019)	(0.016)	(0.548)	(0.598)	(0.690)
log(Firm Age)	-0.326***	-0.344***	-0.171*	-0.496***	-0.472***	-0.429***	-0.480***	-0.563***	-0.429***	-0.010	0.029	-0.045	-0.051*	-0.058*	-0.146***	-0.083**	-0.081**	-0.121**
	(0.064)	(0.073)	(0.094)	(0.079)	(0.083)	(0.082)	(0.084)	(0.088)	(0.082)	(0.030)	(0.031)	(0.035)	(0.031)	(0.033)	(0.031)	(0.039)	(0.042)	(0.049)
log(Sales)$_{t-1}$	0.479***	0.496***	0.454***	0.475***	0.491***	0.236***	0.477***	0.492***	0.236***	0.123***	0.138***	0.130***	0.120***	0.134***	0.048***	0.119***	0.134***	0.128***
	(0.026)	(0.027)	(0.034)	(0.025)	(0.027)	(0.023)	(0.026)	(0.027)	(0.023)	(0.010)	(0.011)	(0.013)	(0.010)	(0.011)	(0.007)	(0.010)	(0.011)	(0.013)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-15,840.8	-10,710.9	-8,769.8	-16,017.1	-10,786.8	-13,877.5	-16,012.7	-10,765.9	-13,877.5	-4,348.5	-3,856.6	-2,755.7	-4,387.9	-3,887.9	-4,364.9	-4,383.9	-3,866.1	-2,775.9
# Firms	9,239	8,496	8,204	9,239	8,496	8,204	9,239	8,496	8,204	9,239	8,496	8,204	9,239	8,496	8,204	9,240	8,496	8,380
# Observations	41,754	39,039	36,534	41,754	39,039	36,534	41,754	39,039	36,534	9,239	8,496	8,204	9,239	8,496	8,204	9,240	8,496	8,380

Notes: This table examines the relationship between publications and industry characteristics across firm age. Firm age is years from date of incorporation. Productivity Growth Dispersion (90-10) is the difference in annual growth rate in productivity between the 90th and 10th deciles within an industry and is based on Acemoglu et al. (2007). External Finance Dependence is defined as the ratio between capital expenditures minus cash flow from operations and capital expenditures and is based on Rajan and Zingales (1998). The Lerner competition index is the industry average ratio between profits and sales. The sample includes firms that have at least one patent or one academic publication in "hard" science journals between 1978 and 2004, have at least 10 employees and at least $1 million in annual sales. The sample in columns 10-18 is cross-sectional for the last year financials are available for each firm. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * significant at 10%; ** significant at 5%; *** significant at 1%.

FIGURE B1: EXAMPLE OF PUBLICATION PAGE FROM THE ISI WEB OF SCIENCE (THOMSON)

Clinical study to assess the immunogenicity and safety of a recombinant Pseudomonas aeruginosa OprF-Oprl vaccine in burn patients

Full Text | Find it Oxford | Holdings | Go | Print | E-mail | Add to Marked List | Save to EndNote Web | more options

Author(s): Mansouri E, Blome-Eberwein S, Gabelsberger J, Germann G, von Specht BU

Source: FEMS IMMUNOLOGY AND MEDICAL MICROBIOLOGY **Volume:** 37 **Issue:** 2-3 **Pages:** 161-166 **Published:** JUL 15 2003

Times Cited: 6 **References:** 28

Abstract: In a recent clinical trial we evaluated the safety and immunogenicity of a recombinant OprF-Oprl vaccine consisting of the mature outer membrane protein I (Oprl) and amino acids 190-342 of OprF of Pseudomonas aeruginosa in burn patients and compared the elicited antibodies with antibodies against tetanus as response to a simultaneous immunization given on the day of admission. Safety and immunogenicity of the vaccine had been tested before in healthy human volunteers as published in 1999. In this first clinical trial we immunized eight burn patients suffering from second or third degree burns involving between 35% and 55% of the body surface three times with 100 mug of the OprF-Oprl vaccine. The vaccine was found to be very well tolerated. The patients did not show any serious side effects - and in particular no activation of the mediator cascade was observed. None of the subjects showed systemic P. aeruginosa infections during or after the treatment of their burns. The serological tests (ELISA) for detection of antibodies against P. aeruginosa and tetanus toxoid showed seroconversion for seven patients after inoculation. The data indicate that OprF-Oprl can be a useful vaccine in the therapeutic management of burn injuries. (C) 2003 Federation of European Microbiological Societies. Published by Elsevier Science B.V. All rights reserved.

Document Type: Article

Language: English

Author Keywords: Pseudomonas aeruginosa; outer membrane protein; vaccine; burn; infectious disease

KeyWords Plus: MEMBRANE PROTEIN-F; HETEROLOGOUS IMMUNOTYPE STRAINS; B-CELL EPITOPES; PROTECTIVE VACCINE; SYNTHETIC PEPTIDES; PORIN PREPARATION; INFECTION; IMMUNIZATION; ANTIBODIES; MODEL

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Publisher: ELSEVIER SCIENCE BV, PO BOX 211, 1000 AE AMSTERDAM, NETHERLANDS

Subject Category: Immunology; Infectious Diseases; Microbiology

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ISSN: 0928-8244

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Note: This figure is an example of a publication page from the ISI Web of Science by Thomson. We systematically matched the name of all Amadeus firms (about 8 million names) to the address field in the publication page. See the text for details about the exact matching process. In addition to the name of the publishing firm, we also use information about the number of citations the publication received, the journal in which it was published, the publication year and the technology area.

Table B1

SUMMARY STATISTICS FOR FIRM PUBLICATIONS ACROSS MAIN FIELDS

Main field	# Publications	Mean Citations Received	Mean Citations Made	Mean of Journal Impact Factor	Average # Authors per publication
All fields	234,707	7.37	16.44	2.14	3.76
Biology & Chemistry	74,422	11.09	21.23	3.11	4.31
Engineering	51,507	3.14	10.44	0.82	2.87
Health & Medicine	48,254	7.55	14.11	2.84	4.36
Physics	22,107	8.35	19.49	2.08	3.97
Materials Science	16,452	5.50	13.72	1.03	3.45
Other	11,319	6.72	18.86	1.29	2.73
Computer Science	10,646	2.58	17.23	0.72	2.72

Notes: This table reports summary statistics for firm publications. Firm publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database (which includes about 20 million publications). The sample covers the period 1978-2004 and includes all Amadeus firms with at least one publication in "hard" science journals (here we do not condition on reporting financials). Mean citations received is the average number of forward citations a publication receives and mean citations made is the average number of citations the publications makes. The journal impact factor is based on the JCR index included in the ISI Web of Science database.

Table B2

SUMMARY STATISTICS FOR FIRM PUBLICATIONS ACROSS MAIN FIELDS:
LARGE FIRMS VERSUS SMALL FIRMS

PANEL A: PUBLICATIONS BY MATURE FIRMS (AGE>21, MEDIAN)

Main Field	Publications	Mean of Citations Received	Mean of Citations Made
All fields	18,575	8.80	16.90
Biology & Chemistry	7,706	13.14	22.68
Computer Science	435	2.85	14.17
Engineering	4,215	2.98	9.27
Health & Medicine	3,428	8.45	15.59
Materials Science	1,536	5.76	12.91
Physics	815	8.44	16.29
Other	440	8.65	16.62

PANEL B: PUBLICATIONS BY YOUNG FIRMS (AGE ≤ 21, MEDIAN)

Main Field	Publications	Mean of Citations Received	Mean of Citations Made
All fields	20,257	7.16	17.62
Biology & Chemistry	6,295	10.45	23.34
Computer Science	1,041	1.52	17.09
Engineering	5,669	4.41	13.20
Health & Medicine	3,686	9.21	16.09
Materials Science	1,681	4.16	13.67
Physics	1,318	7.96	18.33
Other	567	5.09	19.31

Notes: This table reports summary statistics for firm publications, disaggregated according to whether the publishing firm is mature (age above the median) or young (age below the median). The sample covers the period 1978-2005 and includes all Amadeus firms with at least one publication in "hard" science journals that have at least 10 employees and at least $1 million in annual sales. Firm publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database.

Table B3

PUBLICATIONS CHARACTERISTICS ACROSS MAIN FIELDS IN LEADING JOURNAL

PANEL A: PUBLICATIONS BY MATURE FIRMS (AGE>21, MEDIAN)

Main Field	Publications	Mean of Citations Received	Mean of Citations Made
All fields	7,002	11.65	16.47
Biology & Chemistry	3,368	16.55	22.84
Computer Science	67	4.64	9.63
Engineering	1,165	2.05	5.51
Health & Medicine	1,667	9.02	12.03
Materials Science	344	9.52	14.45
Physics	275	10.01	15.98
Other	116	17.74	16.41

PANEL B: PUBLICATIONS BY YOUNG FIRMS (AGE ≤ 21, MEDIAN)

Main Field	Publications	Mean of Citations Received	Mean of Citations Made
All fields	6,394	11.40	18.74
Biology & Chemistry	2,651	14.33	25.04
Computer Science	101	1.09	9.74
Engineering	915	7.31	11.90
Health & Medicine	2,003	10.74	14.30
Materials Science	207	7.25	17.60
Physics	405	10.93	18.01
Other	112	5.89	17.69

Notes: This table reports summary statistics for firm publications in leading academic journals, for mature and young firms. Only publications in journals in the top quartile of the JCR index are included in this table. Firms in the sample have at least 10 employees and at least $1 million in annual sales.

TABLE B4-

SUMMARY STATISTICS FOR FIRM PUBLICATIONS ACROSS COUNTRIES

Country	Publications	Mean of Citations Received	Mean of Citations Made	Mean of Impact Rate of Journal	Average Number of Authors
All Counties	234,864	7.37	16.44	2.14	3.76
Belgium	6,012	7.85	17.17	2.26	4.26
Germany	40,282	6.51	17.20	2.16	3.88
Denmark	1,301	13.60	21.07	3.31	5.07
Spain	5,111	5.62	22.73	2.55	4.84
Finland	2,975	8.12	18.13	1.86	3.77
France	49,804	7.13	18.85	2.08	4.44
Great Britain	85,284	7.58	13.17	2.04	2.97
Greece	584	5.66	18.75	2.24	3.99
Italy	21,380	6.12	17.72	2.43	4.83
Netherlands	8,474	8.43	18.91	2.31	3.84
Norway	4,247	7.29	21.81	1.56	3.34
Sweden	9,410	11.97	17.26	2.28	3.46

Notes: This table reports summary statistics for firm publications across countries. The sample covers the period 1995-2004 and includes all Amadeus firms with at least publication in "hard" science journals between 1978 and 2004. Firm publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database.

TABLE B5-

FIRM PUBLICATIONS IN A SAMPLE OF LEADING SCIENTIFIC JOURNALS

Field	Journal	# of Firms	# of Publications	Citations per Publication	Mean of Employees of Firm
Molecular Biology & Genetics	Cell	8	10	186	12,068
	Nature Genetics	8	14	151	2,286
	Genes & Develpoment	3	4	8	12
	Nature Cell Biology	4	10	57	3,591
	Molecular Cell	2	3	98	808
Physical	Physical Review Letters	93	322	23	3,087
	Physical Review	22	50	32	19
	European Physical Journal	3	13	11	9
	Applied Physics Letters	167	595	22	11,129
	Europhysics Letters	63	107	14	3,856
Biology & Biochemistry	Nature Biotechnology	32	57	35	7,753
	Structure	12	22	51	6,334
	Nature Structural Biology	3	3	94	46,173
	Systematic Biology	1	1	7	2
	Biological Chemistry	17	34	6	8,750
Chemistry	Angewandte Chemie International Edition	67	192	22	11,591
	Analytical Chemisty	94	165	23	5,158
	Journal of Medicinal Chemistry	120	577	26	5,955
	Electrophoresis	57	132	14	6,656
	Chemical Revirews	11	15	64	39,789
Clinical Medicine	Nature Medicine	9	20	72	18,203
	Journal of the American Medical Association	11	20	9	2,338
	European Journal of Clinical Investigation	28	35	21	20,402
	Journal of the National Cancer Institute	16	18	28	10,322
	Lancet Neurology	4	7	9	399
Microbiology	Molecular Microbiology	19	40	22	10,817
	Journal of Virology	39	79	42	6,075
	International Journal of Antimicrobial Agents	43	70	2	4,504
	Applied and Environmental Microbiology	69	171	33	6,968
	Virology	29	51	29	8,635
Immunology	Immunity	10	22	108	1,691
	Journal of Immunology	61	159	39	2,541
	AIDS	51	95	11	4,397
	European Journal of Immunology	54	128	39	3,340
	Journal of Infectious Diseases	6	10	16	983

Notes: This table reports summary statistics on firm publications in selected top academic journals The sample covers the period 1995-2004 and includes all Amadeus firms with at least publication in "hard" science journals between 1978 and 2005. Firm publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database (which includes about 20 million publications).

TABLE B6-

MEASURES OF FINANCIAL DEVELOPMENT ACROSS COUNTRIES

Country	Stock Market Value Traded / GDP	Private Credit / GDP	Accounting standards
Belgium	0.219	0.791	61
Denmark	0.717	1.675	62
Finland	1.288	0.712	77
France	0.717	0.959	69
Germany	0.569	1.229	62
Great Britain	1.898	1.605	78
Greece	0.235	0.788	55
Italy	0.527	0.925	62
Netherland	1.146	1.734	64
Norway	0.591	0.835	74
Spain	1.315	1.255	64
Sweden	1.304	1.117	83
Average	0.877	1.135	68

Notes: This table presents measures of financial developments for the countries in our sample. The first two measures are for 2005 and are based on Beck et al. (2000, 2007). Private Credit is the ratio of private credit by deposit money banks and other financial institutions. Bank Deposits is the demand, time and saving deposits in deposit money banks. Stock Market Value Traded is total shares traded on the stock market exchange. Stock Market Capitalization is the value of listed shares. All measures all divided by the Gross Domestic Product (GDP). Accounting standards is from Rajan and Zingales (1998).