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Corporate Science, Innovation, and Firm Value

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Many firms actively disclose research findings in scientific peer-reviewed journals. The literature highlights several potential benefits of such scientific boundary-spanning activities, including privileged access to academic information networks. However, scientific disclosure may lead to unintended knowledge spillovers. It remains unclear whether active engagement in science leads to higher returns. This paper investigates the impact of scientific activities on the firm's market value, using accounting data for U.S. firms and matched patent and scientific publication data. We find evidence for the positive impact of scientific publications on a firm's market value beyond the effects of research and development, patent stocks, and patent quality, and also document heterogeneity with respect to this impact between different industrial sectors.

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1. Introduction

Research and development (R&D) is an important source of competitive advantage for companies. In particular, investments in upstream research lead to the creation of new knowledge inside a firm and also facilitate the absorption of academic institutions' and researchers' latest knowledge (Cohen and Levinthal 1989, Rosenberg 1990). Consequently, firms investing in research may produce radical inventions, which promise greater financial returns. Interestingly, many companies involved in R&D not only absorb external academic knowledge, but actively contribute to open science by disclosing their own findings in scientific peer-reviewed journals (Hicks 1995).

The literature highlights several mechanisms through which firms who adopt academic disclosure practices might benefit. Broadly summarizing, advantages include increased capacity to absorb external knowledge, the realization of signaling benefits that facilitate access to valuable research inputs such as hiring of Ph.D. graduates, and the promotion of science-based products among professional customers (Hicks 1995, Stern 2004, Polidoro and Theeke 2012). However, the dissemination of research findings in scientific journals may also lead to unintended knowledge spillovers that facilitate imitation by competitors and other specific costs associated with the disclosure process (Arrow 1962, Cockburn et al. 1999, Kinney et al. 2004, Stuart and Liu 2014). Although empirical studies document that firms with scientific publications lodge higher quality patents (Cockburn and Henderson 1998, Gittelman and Kogut 2003, Fabrizio 2009), these studies disregard the potential spillover costs caused by scientific disclosure. It remains unclear, therefore, whether increased R&D productivity by a firm genuinely translates into higher financial profitability.

In this paper, we address this question and investigate the profitability implications of scientific disclosure. To capture all positive and negative effects, we apply a market value approach (Griliches 1981, Jaffe 1986, Hall 1993, Hall et al. 2005). Financial markets react immediately to new information and anticipate future commercial implications. Thus, this approach avoids making assumptions about time lags between knowledge creation, disclosure effects, and the realization of financial returns. We separate—conceptually and empirically—the creation of scientific outcomes from the voluntary disclosure of these outcomes in scientific peer-reviewed journals. We also provide initial insights regarding the broad mechanisms through which scientific publications may create value. A further distinctive contribution is that unlike the majority of studies dealing with science in the corporate context, which refer to the biotechnology and pharmaceutical industries, the present paper considers all high-technology sectors. Since sectors differ according to their appropriability conditions (Levin et al. 1987, Cohen et al. 2000), which may moderate spillover risks of disclosure, we examine sector heterogeneity in greater detail.

Our empirical analysis uses firm-level information from the Compustat database and matched scientific publication and patent data for a representative sample of 1,739 stock market listed firms (9,920 firm-year observations) from all high-technology sectors, covering the period 1996–2006. The results of our econometric analysis suggest a positive relationship between the scientific publications of firms and their Tobin's Q values. We find evidence that disclosure in high-quality journals, which indicates active involvement in science, is especially valuable in terms of higher stock market premiums. However, we detect a certain degree of heterogeneity across high-technology sectors: whereas scientific publications are associated with positive returns in the instruments sectors, and to some extent also in pharmaceutical and biotechnology sectors, we find a negative but nonsignificant tendency in the information and communication technology (ICT) sectors.

2. Theoretical Background

This paper builds on the already large body of literature examining the relationship between R&D and market value, and on recent work investigating the scientific activities of profit-oriented firms. With regard to the former, several studies have examined the impact of R&D expenditures, patent stocks, and patent quality indicators on firm value (for surveys, see Hall 2000, Czarnitzki et al. 2006; Hall et al. 2005). The majority have highlighted a positive effect of R&D and patent stocks on the firms' market value, including a premium for high-quality patents. More recent studies have taken into account the strength of the appropriability regime, complementary assets, and knowledge spillovers as moderating factors on this impact (Cockburn and Griliches 1988, McGahan and Silverman 2006, Belenzon 2012). To date however, few studies have considered heterogeneity of R&D activities across firms. One exception to this in accounting literature is the study by Deng et al. (1999), who found a positive effect of executing scientific research on firm value. However that study did not analyze voluntary contributions of firms to the stock of open science. Instead, the authors relied on nonpatent literature (NPL) references in a firm's list of patents as a proxy for scientific research. We build on their work and offer a more complete perspective, with a special focus on the impact of the active participation of firms in the scientific community, tangibly reflected in scientific publications.

From a conceptual point of view, there are several reasons why the scientific activities of firms may have implications for firm profitability. Firms engaging in (basic) research may develop superior capabilities, in that they may be able to combine technologically distant knowledge to create inventions that are more valuable than those created by other firms. Such firms are potentially able to absorb external knowledge and identify promising trajectories for applied research and experimental development, leading to superior inventive outcomes (Rosenberg 1990, Cohen and Levinthal 1989, Gittelman and Kogut 2003, Fleming and Sorenson 2004, Fabrizio 2009). Although these studies also suggest a positive relationship between research investments and firm profitability, the potential costs of basic research are not considered. In particular, basic research findings do not necessarily lead to high commercial success since translating findings into concrete products can be challenging (see Nelson 1959, Rosenberg 1990, Cockburn et al. 1999, Pisano 2006).

Beyond the creation of scientific knowledge, many firms also voluntarily disclose their research results in scientific journals. Such involvement in open science may create value through several mechanisms associated with access to upstream knowledge and appropriation (for a review, see Penin 2007). With regard to upstream knowledge, disclosing research results may not only increase the absorptive capacity (Cockburn and Henderson 1998), but may facilitate knowledge sourcing from academic scientists, thanks to reciprocity in knowledge exchange. More specifically, academic scientists may be reluctant to interact with scientists from firms unless the latter share valuable research results (Hicks 1995, Simeth and Raffo 2013). Moreover, scientific publications can be leveraged as a human resource instrument with regard to Ph.D. graduates. Many scientists who consider the private sector as a career option value the possibility of continuing publication activities, and may seek out firms engaging in this practice (Stern 2004, Sauermann and Roach 2013). Scientific publications are also considered a potential appropriability device. Disclosure may encourage the adoption of science-based products such as medical drugs or instruments (Azoulay 2002, Polidoro and Theeke 2012). Clinicians, as users of medical instruments, influence procurement decisions in university hospitals and are keen to understand the technological characteristics of the products. Manufacturers of such devices might gain greater credibility among these clinicians by disclosing related information in scientific peer-reviewed journals. Another appropriation-related use of scientific documents is the establishment of prior art through disclosure, the aim being to hamper patenting strategies of competitors working on similar inventions (De Fraja 1993, Parchomovsky 2000, Della Malva and Hussinger 2012).

However, the publication process has related costs. The most obvious of these are unintended knowledge spillovers that may enable competing firms to learn from the disclosed knowledge (Arrow 1962). Knowledge spillovers may reduce the cost of imitation for competitors, and offer the latter insights into future trends and facilitate their exploration of alternative technological trajectories. In addition, the publication process itself can lead to opportunity costs since a firm's researchers have to prepare documents that meet the publishing requirements set down by journals, interact with referees, and codify tacit knowledge (Kinney et al. 2004). Furthermore, firm scientists who publish are more visible to competing firms, which may impose the need for retention strategies as their external employment options increase (Stuart and Liu 2014, Kim and Marschke 2005). In summary, the positive and negative effects of the relationship between corporate science and firm value underline the need for further study in this area.

3. Data and Methodology

3.1. Data Sources

Our analysis was based on a sample of U.S. public companies from high-technology industries, as defined by the Organisation for Economic Cooperation and Development (2011), including pharmaceuticals and biotechnology, telecommunication equipment and semiconductors, aircraft, as well as scientific and medical instruments. We also included the chemicals sector since it is often recognized as science oriented. These industries were natural choices because they draw on scientific knowledge as an input factor, but their publication output is varied (Cohen et al. 2002, Simeth and Raffo 2013). Firm-level data came from Standard and Poor's Compustat, patent data came from the Worldwide Patent Statistical Database (Patstat, version April 2014) provided by the European Patent office, and publication data came from Elsevier's Scopus database. Because coverage of Scopus increased considerably in 1996, we were obliged not to include earlier periods in our analysis.[1] Moreover, the patent information concerning the U.S. Patent and Trademark Office patents contains the caveat that applications filed before November 29, 2000, but not granted are unobservable.[2] To keep the numbers of patents comparable over time, we considered only patent applications where we observed the grant within seven years after the application date. This allowed for the inclusion of patent data until 2006. Consequently, the sample covers the time period 1996–2006, and firms were considered for selection based upon the criterion that they invested in R&D in at least one of the years during this period.

Combining firm-level data with publication and patent information may lead to errors arising from name-based matching procedures. To achieve high recall rates of publication and patent numbers, we carefully precleaned all firm names by correcting misspellings and removing abbreviations denoting corporate structure (e.g., "Inc."). The publication and patent matching processes differed, as scientific publications were retrieved manually from the Scopus online database, whereas patent data were matched using an off-line source. The former is a more time-consuming process than "automatic" off-line matching, and the latter requires extensive manual cleaning of the algorithm-based matching results. Manual retrieval of publication data enabled us to directly inspect hits and immediately exclude other institutions with an identical name. The process is explained in further detail in §A1 of the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2015.2220). For the off-line matching procedure with patent data from the Patstat database, we first pretested all names to detect problematic cases. Firms with ambiguous names were either excluded directly or marked for detailed manual inspection once the actual matching took place. Second, we applied name standardization routines both to the names of our sample firms and the applicant field in the Patstat database. Third, after testing several matching algorithms, we identified the one that achieved the highest recall rate while simultaneously limiting false positive hits (see Raffo and Lhuillery 2009). The resulting matches were checked manually with particular focus on firms with atypical input–output ratios and those identified in the pretests as being uncertain. To crosscheck the quality of our patent-matching process, we also combined our data with the Compustat-National Bureau of Economic Research (NBER) data set (see Hall et al. 2001), performing regressions on the patent numbers based first on our matching and then on Compustat-NBER matching. The results were consistent. Since the Compustat-NBER data set also considers static ownership structure (for the year 1989), this exercise suggests that our results were not affected by our inability to take into account subsidiaries of the studied companies in the present study. However, it is still theoretically possible that we missed a relevant number of publications when not considering subsidiaries. To mitigate such concerns, we searched for information on subsidiaries for some of the investigated sectors (biotech, Standard Industrial Classification (SIC) codes 2845 and 2846; semiconductors, SIC code 3674; instruments, SIC codes

[1] See Elsevier (2014) for further information on content coverage of the Scopus database.

[2] Except patents that entered into the Patent Cooperation Treaty (PCT) procedure for worldwide protection.

3841 and 3842) and downloaded publications taking into account the names of the subsidiaries using the SEC security filings (report "10-K"). The corresponding regressions suggested that no bias arose from the non-consideration of subsidiaries in our analysis (see §A2 in the online appendix).

To reduce biases originating from merger and acquisition (M&A) activities, measurement errors, and "atypical" firms (e.g., specialized R&D firms with a majority of shares owned by business groups), several filters were applied to the sample. First, to limit potential biases from M&A events, firms with large changes in book value were identified based on the criteria of an increase of more than 300% or decrease of more than 75% over a period of two consecutive years (Griliches 1981, Hall and Oriani 2006, Aldieri and Cincera 2009). We dropped the firm-year observation only when a large change occurred. In such cases, we treated the firm in subsequent years as a new firm (Griliches and Mairesse 1984). Excluding firms involved in M&A activities entirely could have led to selection bias since M&A activities are presumably often based on successful R&D operations. To address measurement errors and inaccurate initial knowledge stock computations, we also dropped observations with extremely high (the top 1%) knowledge-to-asset ratios.[3] Finally, we excluded firms with fewer than 10 employees, imposed a minimum sales amount of USD 500,000, and removed firms with an R&D/sales ratio higher than one. A firm with no sales generates a high degree of uncertainty among investors in terms of its survival prospects. Such firms are therefore at a different structural stage than those already generating a cash flow, the result likely being heterogeneous treatment on the stock market. In our study, since the R&D/sales ratio filter affected a notable number of observations, we removed it as a robustness test (see §4.4). The final sample size contained 9,920 firm-year observations, composed as shown in Table 1.

Finally, all financial amounts were adjusted for inflation using the gross domestic product (GDP) deflator.

3.2. Variables

To construct our dependent variable, we applied the methodology followed by previous related research and used Tobin's Q, which represents the ratio of a firm's market value to its book value. Market value is the addition of the market value of the equity and the market value of the debts. The former is calculated by the number of outstanding shares multiplied by the stock price at the end of the fiscal year, whereas the latter is approximated using the

[3] The three measures concerned are $R\&D/A$, $PAT/R\&D$, $PUB/R\&D$, which are explained in detail in §3.2.

Table 1 Observations According to Included Sectors

Metasector	SIC included	Firm-year observations
Biotechnology and pharmaceuticals	2834, 2835, 2836	1,602
Chemicals	2800, 2810, 2820, 2821, 2833	389
Information and communication technologies	3570, 3571, 3572, 3575, 3576, 3577, 3578, 3579, 3661, 3663, 3669, 3670, 3672, 3674, 3677, 3678, 3679, 4812, 4813, 4822	4,373
Aircraft and aerospace	3721, 3724, 3728	166
Navigation, scientific, medical, and optical instruments	3812, 3822, 3823, 3824, 3825, 3826, 3827, 3829, 3841, 3842, 3843, 3844, 3845, 3851, 3861	3,390
Total		9,920

book value of liabilities (Blundell et al. 1999, Hall and Oriani 2006, Ceccagnoli 2009). The firm's book value is represented by its assets at the end of the fiscal year. With respect to the independent variables, one core measure is the firm's R&D investments, which reflect overall commitment to knowledge production. The investments in R&D take place in a particular period, but the returns on these investments may last much longer. Therefore, we introduced a stock measure of R&D. Since knowledge becomes obsolete because of ongoing technological development, we applied the frequently used perpetual inventory method with an annual 15% depreciation (δ) rate (Griliches and Mairesse 1984, Hall et al. 2005). In the absence of a strong theoretical justification for assuming different rates for the other knowledge-related measures, we not only computed the R&D stock, but also the publication and patent stock indicators for firm i in period t with the 15% rate as follows:

$$R\&D\ STOCK_{it} = R\&D_{it} + (1-\delta)R\&D\ STOCK_{it-1}. \quad (1)$$

Although the computation of the R&D stocks is technically straightforward, assumptions have to be made regarding the initial stock ($R\&D\ STOCK_{it0}$), which remains partly unobserved. In our study, we applied a standardized growth rate (g) for R&D and the other knowledge stock measures of 8%, given that our sample contained only high-technology firms (Hall and Oriani 2006, Hall et al. 2007).[4] All knowledge-related measures discussed below are accordingly constructed as stocks. We constructed three measures directly related to the firms' scientific operations. First, we use a patent-based indicator to measure outcomes from basic research, and

[4] This applies specifically to firms that do not have a long presample record in *Compustat*. The stocks can be (at least partly) computed with observed values for firms with IPO's before 1996. In formal terms, the initial R&D stock is approximated as follows: $R\&D\ STOCK_{it0} = R\&D_{it0}/(\delta + g)$.

thus indirectly also measure a firm's potential to create scientific publications (*SCIPAT*). It is assumed that the existence of a scientific document in the backward references of a patent indicates a science-based patent (Narin et al. 1997, Deng et al. 1999). We identified scientific documents in the NPL section of patents' backward references using specific keywords and character combinations collected via extensive screening of the raw NPL information. Since this measure captured research outcomes but did not depend on the observation of scientific contributions to academic journals, the use of *SCIPAT*, in combination with the publication-based indicators, enabled us to differentiate between research outcomes and disclosure effects.[5] Although this measure of basic research relies on patented outcomes, we nonetheless considered it to be a reasonable measure, given that our sample comprised only firms from high-tech sectors with a high propensity to patent.

Second, we captured the number of voluntary scientific contributions by computing a stock measure based on the number of scientific papers published by each firm (*PUB*). Given our use of *SCIPAT* to measure basic research outcomes, the publication stock should not only reflect research productivity, but also effects deriving from the disclosure of results. Moreover, to consider the heterogeneity of scientific contributions, we introduced a second measure reflecting their academic quality (*TOPPUB*). If firms are able to publish in prestigious journals, it is likely that the degree of involvement in the scientific community will be higher. Publishing in highly ranked journals is also less likely to reflect appropriation motives since the publication process is riskier with higher likelihoods of rejections and delays imposed by referees' requests for further experiments before accepting the submitted article. To overcome potentially imperfect corrections for field effects and inaccurate weightings of articles by impact factors, we decided to rely on a simpler dichotomous distinction by identifying the top 10% of journals based on the impact factor distribution within the five metadisciplines: life sciences, physical sciences and engineering, social sciences, health sciences and general/interdisciplinary. The computed stock variable therefore considered only scientific documents published in these top journals (see §A3 in the online appendix).

In line with previous literature, we included two measures reflecting the amount of inventive outputs and their quality. The absolute amount of inventive outcomes is represented by patent stocks (*PAT*), and the quality of the inventive outcomes (*FWDCIT*) is measured using forward citation counts (Hall et al. 2005). To deal with the truncation problem of citation counts, we considered only those citations that occurred within a five-year window after the priority date of our focal patents (Lanjouw and Schankerman 2004, Marco 2007). Finally, we included sector and year dummy variables to take into account heterogeneous market valuations across industries and time (Cockburn and Griliches 1988, Hall et al. 2005).

3.3. Model and Estimation Techniques

In this paper, we analyze the relative market value of firms (Tobin's Q) as a function of their knowledge stocks. We rely on the well-established market value function (Griliches 1981, Hall et al. 2005), which regards tangible (A_{it}) and intangible assets (K_{it}) as additives ("hedonic model"). The function can be formalized as follows:

$$V_{it}(A_{it}, K_{it}) = q_{it}(A_{it}, \gamma K_{it})^{\sigma}. \tag{2}$$

In this equation, q_{it} represents the valuation coefficient of a firm's assets, and the parameter γ allows for the eventuality that knowledge assets are valued differently from physical assets. The valuation coefficient q_{it} may vary across time and industries and also contains a firm-specific component. The factor σ represents scale effects and is assumed to equal 1 (Hall et al. 2005), which is also confirmed in our data. Applying logarithms on both sides and moving tangible assets to the left-hand side of the equation yields the following expression:

$$\log\left(\frac{V_{it}}{A_{it}}\right) = \log Q = \log q_{it} + \log\left(1 + \gamma \frac{K_{it}}{A_{it}}\right) + e_{it}. \tag{3}$$

Following our theoretical discussion, we separate the knowledge intangibles of firms into R&D, patent stocks, and publication stocks. Since patents and scientific publications can be regarded as direct outcomes of R&D inputs, we introduce these additional measures as ratios denominated by R&D expenditures (Hall et al. 2005, 2007; Hall and Oriani 2006), formalized in Equation (4):

$$\log\left(\frac{V_{it}}{A_{it}}\right) = \log Q = \log q_{it} + \log\left(1 + \gamma_1 \frac{R\&D_{it}}{A_{it}} + \gamma_2 \frac{PAT_{it}}{R\&D_{it}} + \gamma_3 \frac{PUB_{it}}{R\&D_{it}}\right) + e_{it}. \tag{4}$$

In our empirical setting, *R&D*, *PAT*, and *PUB* represent the respective stock measures computed using the perpetual inventory method with an assumed depreciation rate of 15%. In the full specification, we distinguish between the impacts of (*basic*) *research* and

[5] Taking into account the possibility that *SCIPAT* might not exhaustively capture the basic research outcomes, we also included a stock of "original" patents based on the patent originality measure proposed by Trajtenberg et al. (1997). The results of this specification are reported in §A4 of the online appendix and are consistent with those of the main model.

Table 2 **Summary Statistics**

Variable	*N*	Mean	Std. dev.	Median	Min	Max
Tobin's Q	9,920	2.65	2.39	1.89	0.25	23.02
A (*book value*)	9,920	1,548.56	7,172.64	94.33	0.55	273,007.30
R&D (*flow*)	9,920	104.29	468.25	8.36	0.00	12,942.19
R&D (*stock*)	9,920	491.47	2,082.16	39.96	0.00	41,408.40
R&D/A	9,920	0.61	0.71	0.39	0.00	7.42
PAT (*stock*)	9,920	114.33	559.85	5.57	0.00	9,969.30
PAT/R&D	9,920	0.31	0.46	0.15	0.00	3.68
SCIPAT/PAT	9,920	0.27	0.31	0.17	0.00	1.00
FWDCIT/PAT	9,920	5.59	7.50	4.38	0.00	198.65
PUB (*stock*)	9,920	69.54	347.81	1.77	0.00	6,440.20
PUB/R&D	9,920	0.15	0.29	0.04	0.00	2.85
TOPPUB/PUB	9,920	0.20	0.29	0.00	0.00	1.00
SALES	9,920	1,229.41	5,248.79	79.41	0.50	88,784.06
EMPLOYEES	9,738	4,076.93	14,324.04	340.00	10.00	238,000.00

Note. Monetary amounts in USD millions (in 2005 prices, GDP deflated).

disclosure effects using further measures that are introduced as ratios and that are orthogonal to the main variables. These further variables reflect science-based inventions (*SCIPAT/PAT*), the quality of the inventive output (*FWDCIT/PAT*), and the academic impact of scientific output (*TOPPUB/PUB*). Consequently, the extended model of Equation (4) can be written as

$$\log\left(\frac{V_{it}}{A_{it}}\right)=\log Q=\log q_{it}+\log\Bigg(1+\gamma_1\frac{R\&D_{it}}{A_{it}} +\gamma_2\frac{PAT_{it}}{R\&D_{it}}+\gamma_3\frac{PUB_{it}}{R\&D_{it}}+\gamma_4\frac{SCIPAT_{it}}{PAT_{it}} +\gamma_5\frac{FWDCIT_{it}}{PAT_{it}}+\gamma_6\frac{TOPPUB_{it}}{PUB_{it}}\Bigg)+e_{it}. \quad (5)$$

Equations (4) and (5) can be directly estimated using nonlinear least squares (NLLS). Instead, ordinary least squares (OLS) regression models can be applied only by using the approximation $\log(1+x)\sim x$. Nevertheless, higher values of x lead to imprecisions in the estimated outcome. An important concern is the potential presence of unobserved firm heterogeneity. However, independent variables are potentially predetermined since past firm valuations may influence current investment decisions related to R&D strategies. This eventuality violates the strict exogeneity assumption for the "within" estimator. Moreover, unlike the rather volatile Tobin's Q indicator, the innovation-related variables change slowly over time and are thus highly correlated with the firm-specific effect. Consequently, a "within" fixed-effects estimator may rather exacerbate estimation problems than allow valid estimates to be obtained (see also Hall et al. 2005). A potential solution, suggested by Blundell et al. (1999), is the introduction of a prestock average of the firm's market value as an additional regressor. We tested this approach, but it led to a substantially decreased sample since many firms do not have a sufficiently long stock market history. Consequently, like most of the related empirical literature, we decided to focus on NLLS regression models.

3.4. Descriptive Statistics

In Table 2 we provide an overview of the mean and median values as well as the standard deviation of the regression variables and selected additional measures that provide information about firm characteristics.

Since all firms were stock market listed, the sample consisted predominantly of medium- and large-sized firms. However, median values suggest considerable heterogeneity among our sample of firms. The median values for annual R&D expenditures were USD 8.36 million, USD 79.41 million for sales, and 340 for the number of employees, whereas the mean values were much higher, indicating the presence of both large but also medium-sized and small firms. The average Tobin's Q ratio was quite high at 2.65. In 12.3% of the firm-year observations, the market valuation was below the book value.

Time trends with regard to publication and patent outputs are shown in Figures 1 and 2. The average number of publications and patents by a firm both increased over time. At the beginning of the sample period, the number of patents continuously increased, whereas the number of publications remained stagnant, before starting to increase in 2002. Interestingly, the average levels of publication and patent activity did not differ greatly, which is remarkable given that firms are, by definition, not concerned with contributions to the stock of scientific knowledge per se. With regard to the share of firms with at least one publication or patent in a given year, we obtained the following picture as reported in Figure 2: the share of publishing firms increased from 37% in 1996 to 53% in 2006, whereas the share of patenting firms increased from 46% in 1996 to 60% in 2006. Output types appeared to be complementary since the

Figure 1 (Color online) Average Publication and Patent Outputs

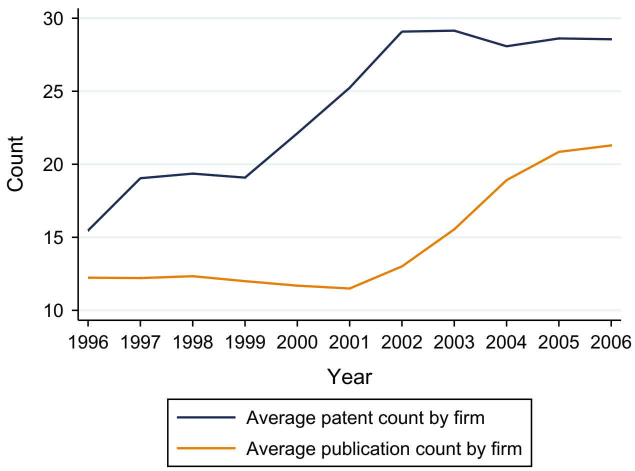
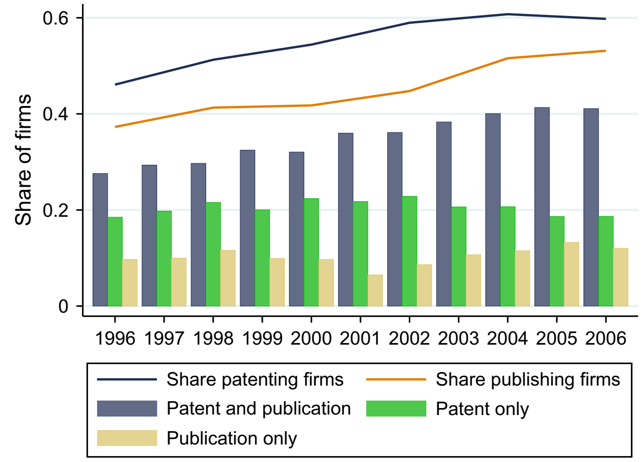


Figure 2 (Color online) Share Publishing and Patenting Firms



majority of publishing firms in a given year also filed a patent application. Over time, there was an increase in the strategy to patent and publish simultaneously. In 2006 however, 14% of all firms only published, 17% only created patents, and 26% of firms neither created patents nor published.

4. Econometric Results and Discussion

4.1. Full Sample Estimations

The core specifications of the econometric analysis are shown in Table 3. Considering the elements highlighted in the previous section, we estimated Tobin's Q with both nonlinear and linear regression models, but ultimately focused on the interpretation of the former since nonlinear models enable the theoretical model to be directly represented. To evaluate the quantitative impact of our variables in the NLLS regressions, we also computed semielasticities (at the mean values of the variables), which are reported in complementary columns for the baseline (2) and full (6) NLLS regression models.[6]

In columns (1) and (2), we estimated baseline specifications using NLLS and OLS estimators. All three knowledge measures representing R&D ($R\&D/A$), patent ($PAT/R\&D$), and publication ($PUB/R\&D$) stocks had a positive and significant effect on Tobin's Q, the latter two having similar magnitudes. One additional patent per million dollars of R&D was associated with an increase of 9% in Tobin's Q and 10% for an additional publication per million dollars of R&D. This result provided a first indication that scientific activities have an important impact on the market value of firms. To obtain a more detailed picture, we introduced the additional measures described in §3.3. In columns (3)–(5), we first separately added the three variables *FWDCIT/PAT*, *SCIPAT/PAT*, and *TOPPUB/PUB* to the baseline model. All three measures exhibited a value premium for Tobin's Q. The main variables remained statistically significant when the supplementary patent-based variables were included. However, when adding the measure capturing the share of publications in prestigious journals (*TOPPUB/PUB*) in column (5), the magnitude of the publication stock $PUB/R\&D$ decreased, and the variable only remained significant at the 10% level. In columns (6) and (7), we report the regression results with the full variable set. In the NLLS specification (6), it can be seen that R&D stocks, patent stocks, and patent citation stocks (*FWDCIT/PAT*) had a positive impact, which is in line with findings from previous studies (e.g., Hall et al. 2005). Although publication stocks ($PUB/R\&D$) were significant only at the 10% level, we detected a strong positive and highly significant effect of publications in top journals. The increase of the variable by one unit—which is equivalent to a change from none of a firm's publications being in top journals to all of the firm's publications being in top journals—increased Tobin's Q by approximately 12%.[7] Interestingly, the impact of science-based patents (*SCIPAT/PAT*) became substantially weaker in comparison to column (4), with the positive effect of a one unit change decreasing from 11% to 4% and the variable becoming statistically insignificant once the share of publications in top journals was taken into account.

[6] Semielasticities can be obtained by calculating the derivative of the estimated market value equation with regard to the variable of interest. See Hall et al. (2005) for further details.

[7] Caution must be exercised when comparing the magnitudes between $PUB/R\&D$ and *TOPPUB/PUB* due to the different units of the variables. Therefore, we also calculated the impact of a change by one standard deviation. The result of this exercise also suggested that publications in prestigious journals are associated with a particularly strong increase in Tobin's Q (3.7% versus 1.6%).

Table 3 Regression Outputs

Log *Tobin's Q*	(1) OLS	(2) NLLS		(3) NLLS	(4) NLLS	(5) NLLS	(6) NLLS		(7) OLS
	Coeff (SE)	Coeff (SE)	Semielast.	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Semielast.	Coeff (SE)
R&D/A	0.048***	0.055***	0.051	0.055***	0.052***	0.051***	0.050***	0.045	0.042***
	(0.011)	(0.014)		(0.015)	(0.014)	(0.014)	(0.015)		(0.011)
PAT/R&D	0.083***	0.097***	0.090	0.071***	0.083***	0.097***	0.072***	0.064	0.066***
	(0.021)	(0.025)		(0.026)	(0.025)	(0.025)	(0.026)		(0.021)
PUB/R&D	0.095***	0.110***	0.102	0.108***	0.091**	0.066*	0.065*	0.057	0.056*
	(0.032)	(0.039)		(0.039)	(0.039)	(0.038)	(0.039)		(0.032)
FWDCIT/PAT				0.007***			0.006***	0.005	0.004**
				(0.002)			(0.002)		(0.002)
SCIPAT/PAT					0.124***		0.046	0.041	0.052
					(0.035)		(0.037)		(0.032)
TOPPUB/PUB						0.168***	0.142***	0.126	0.125***
						(0.040)	(0.041)		(0.034)
Firm-year observations	9,920	9,920		9,920	9,920	9,920	9,920		9,920
Firm-IDs (cluster)	1,739	1,739		1,739	1,739	1,739	1,739		1,739
R^2	0.129	0.130		0.136	0.134	0.136	0.141		0.141

Notes. Standard errors (clustered by firm) are reported in parentheses. All regression models contain year and SIC four-digit industry dummies. The semielasticities reported in the table are computed at the mean values of the variables. The semielasticities of the stepwise introduced variables in columns (3)–(5) are as follows: *FWDCIT/PAT*, 0.007; *SCIPAT/PAT*, 0.113; and *TOPPUB/PUB*, 0.153.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Based on these regression results, the question arises as to whether the positive effects of scientific activities that we found reflect (i) the successful creation of science-based knowledge outcomes or benefits that derive from the disclosure of these outcomes, (ii) signaling benefits to academic audiences or the use of publications as a device to support appropriation. We would like to stress that we cannot provide conclusive evidence concerning these mechanisms with our measures, but can only offer some indications, which must be treated with caution. In the full model presented in column (6), positive effects for scientific publication stocks and especially top journal publications were observed despite the presence of science-based patents. Although being highly significant and exhibiting a notable magnitude in column (4), the measure of science-based patents was no longer significant in the full specification. This indicates that the use and absorption of basic research has a positive impact on a firm's market value. However, active involvement in science, which is especially represented by publications in top journals, generates a considerable market value premium beyond the successful absorption of scientific knowledge. The relevance of publication quality also has implications with regard to point (ii) above and the underlying value-creating mechanisms of scientific disclosure. Firms that disclose knowledge for defensive purposes have an interest in keeping control over the timing of disclosure. As a consequence, there are incentives for firms to target lower-impact journals because, presumably, the likelihood of acceptance in high-impact journals is lower and the time taken to publish longer. Therefore, if this mechanism is value enhancing, we would expect a stronger effect of the main publication stock *PUB/R&D* in the full model. However, the particularly strong effect of publications in high-impact journals points more to value deriving from facilitated interactions with academic partners. In other words, firms actively participating in the scientific community seem to have easier access to valuable knowledge and to highly qualified graduates, which results in a higher Tobin's *Q*.

4.2. Sector Analysis

Since the association between scientific activities and firm value may differ across industries, especially in the light of the relative risks of knowledge spillovers, we analyzed the individual sectors in greater detail. In Table 4, we report the results of subsample regressions with the metasectors biotechnology and pharmaceuticals (hereafter, BIO-PHARM), information and communication technologies (ICT), scientific and medical instruments (INST), and chemicals (CHEM).

Starting with the baseline specification, it can be seen that the effect of scientific publication stocks differs across the metasectors. Although we detected a positive but nonsignificant sign in BIO-PHARM and CHEM, a negative and nonsignificant effect was found in ICT, whereas a positive and significant effect was observed for the INST sectors. Estimating the regression model with the full set of variables revealed interesting patterns. In BIO-PHARM,

Table 4 Heterogeneity by Sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BIO-PHARM		ICT		INST		CHEM	
Log *Tobin's Q*	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS
	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)
R&D/A	0.126***	0.108***	0.022	0.022	0.086***	0.075**	0.395*	0.389*
	(0.040)	(0.041)	(0.017)	(0.018)	(0.029)	(0.030)	(0.208)	(0.206)
PAT/R&D	−0.040	−0.028	0.142***	0.110**	0.103***	0.079**	0.067	−0.010
	(0.067)	(0.075)	(0.049)	(0.048)	(0.036)	(0.038)	(0.115)	(0.094)
PUB/R&D	0.133	0.045	−0.009	−0.014	0.218***	0.149**	0.115	0.058
	(0.088)	(0.086)	(0.049)	(0.050)	(0.075)	(0.075)	(0.169)	(0.140)
FWDCIT/PAT		0.006		0.003		0.009*		0.022
		(0.007)		(0.002)		(0.005)		(0.020)
SCIPAT/PAT		−0.037		0.129**		0.021		−0.098
		(0.074)		(0.058)		(0.070)		(0.141)
TOPPUB/PUB		0.225**		−0.015		0.243***		0.026
		(0.090)		(0.054)		(0.077)		(0.137)
Firm-year observations	1,602	1,602	4,373	4,373	3,390	3,390	389	389
Firm-IDs (cluster)	331	331	762	762	565	565	57	57
R^2	0.071	0.088	0.120	0.127	0.129	0.156	0.136	0.150

Notes. Standard errors (clustered by firm) are reported in parentheses. All regression models contain year and SIC four-digit industry dummies. Regression models represent baseline and full model specifications for metasectors biotechnology and pharmaceuticals (BIO-PHARM) in columns (1) and (2), information and communication technologies (ICT) in columns (3) and (4), instruments (INST) in columns (5) and (6), and chemicals (CHEM) in columns (7) and (8). See Table 1 for information on SIC codes included in the metasectors. The regression results for the aircraft sector are omitted in this table due to the very low number of observations. The semielasticities of the publication-based measures are as follows: *PUB/R&D*, 0.039 in column (2), −0.014 in column (4), 0.125 in column (6), 0.058 in column (8); *TOPPUB/PUB*, 0.195 in column (2), −0.014 in column (4), 0.204 in column (6), and 0.022 in column (8).

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the publication quality indicator was significant and of quite a strong magnitude, whereas the variables reflecting the main publication stock and science-based patents did not have such an impact. This result suggests that as long as a firm is not seriously committing to open science, scientific activities will not be sufficient to generate a value premium. We observed a similar result for the INST subsample, where the *TOPPUB/PUB* measure had a strong positive effect too. However, the main publication variable *PUB/R&D* also showed a rather strong magnitude compared to the other subsamples, and remained significant. This finding suggests that in addition to upstream signaling, publications may create value through mechanisms other than establishing knowledge flows with the scientific community. One plausible interpretation for this finding lies in marketing effects, since firms in instrument sectors sell to scientifically trained professional customers. To establish credibility among this audience with regard to the latest science-based products, publishing in high-impact journals is presumably less crucial. In the ICT domain, we saw a different picture. Publication stocks were negative and the share of top impact journal publications also had a negative sign. Interestingly, in addition to the positive effects of patent stocks and patent quality, the share of science-based patents was positive and significant. In other words, absorbing scientific knowledge and achieving science-based inventions may create value, whereas active dissemination of results and participation in the scientific community do not. For the chemical sector, we only observed a positive effect of R&D on the market value. However, there was no premium for patent and publication stocks or for science-based patents.

These obtained differences across sectors indicate that appropriability conditions have a notable influence on the returns of scientific disclosure strategies. In sectors with strong legal appropriation, like the medical instrument and biopharmaceutical industries, we observed positive net returns from scientific publications, whereas in the ICT domain, which can be characterized as having a weaker appropriability regime due to its complex and cumulative nature, no premium was observed (see Levin et al. 1987, Cohen et al. 2000, Hall and Ziedonis 2001). This finding suggests that in the ICT sectors, scientific disclosure leads to knowledge spillovers that outweigh any benefits. The result for the chemical sector, where appropriability conditions are stronger than those in the ICT sector, can be explained by the fact that in the former, academic knowledge is only of moderate importance as an input. Therefore, the potential benefits of scientific disclosure in terms of signaling might be limited in the first place.

4.3. Robustness Tests

Beyond considering subsidiary publications for a subsample of firms, as reported in §A2 of the online appendix, we performed further robustness checks, the most important of which are displayed in §A4 of the online appendix. These robustness tests did not change our main models' results. Consequently, we will only describe them very briefly. We list several tests, and for ease of reading, we shall assign them numbers that correspond to the respective columns in §A4 of the online appendix: (1) We ran fixed-effect regression models. As discussed in §3.3, such models must be interpreted with caution in our context. However, the results suggested that scientific activities do indeed lead to higher firm values. (2) We removed the filter which initially excluded firms whose R&D/sales ratio was larger than one since this filter was perhaps overly restrictive. However, our results after removing this filter did not change. (3) To control for unobserved selection mechanisms for publication in terms of local spillovers and competition, we included state dummies. (4)–(5) Since scientific backward references may not exhaustively capture basic research outcomes in firms, we included the patent originality variable as suggested by Trajtenberg et al. (1997). This variable behaves very similarly to science-based patents and supports the interpretation that the results for publication stocks do not only reflect research productivity effects, but also benefits deriving from the active involvement of firms in science. (6)–(8) We introduced additional control variables, namely, the amount of sales and the growth of sales, sector-level patent and publication propensities, and the share of firm profit of the industry profit. These controls should capture the effect of unobserved intangibles potentially correlated with our knowledge intangibles, of the abilities of firms to appropriate returns from R&D, and in the case of the sector-level variables, of incentives to engage in publication. Our results did not change when these additional controls were included. (9) We used the patent counts from the Compustat-NBER matching (Hall et al. 2001, Cockburn et al. 2009) to verify the quality of our own matching. The regression outputs were very similar. (10)–(11) We modelled the market value function in a different way by including the publication stock to patent stock ratio (i.e., instead of publication stock to R&D stock ratio) for the subsample of patenting firms. Such a specification might be an adequate measure of openness if publications and patents reflect the same knowledge. The variable *PUB/PAT* was found to be positive and significant, supporting the interpretation of the core models that publication provides additional value beyond patented knowledge. (12) We included an additional measure of the share of publications coauthored with academic institutions. This variable had a positive but not significant effect when added to the model with the full set of variables.

5. Conclusion

This study examines the impact of scientific activities of firms on their stock market valuation using a data set of firm-level information for U.S. high-technology companies, combined with scientific publication and patent data. Although scholars have recently started to conceptually and empirically address the determinants of scientific activities by firms, particularly disclosure, there are very little data for firm performance effects. Thanks to its design, our analysis provides an empirical contribution not only to the growing literature on boundary-spanning activities of firms, but also to more mainstream studies assessing the performance implications of R&D in firms.

Our analysis documents the positive impact of science-related indicators on a firm's market valuation beyond the effects of R&D and inventive outcome indicators. Our measures enabled us to differentiate between the profitability implications of performing research and a more active involvement in open science. Although we cannot entirely rule out the possibility that we also capture research productivity effects, our findings suggest that active involvement in science, as reflected by disclosure in scientific journals, results in higher stock-market values. Furthermore, our results indicate in particular that the positive effects of such disclosure stem from scientific signaling to upstream stakeholders, which results in superior knowledge flows from these persons and institutions. In other words, publishing allows firms to become members of the scientific community and to establish formal and informal interactions, which in turn provide the former with access to state-of-the-art developments and research techniques. On the other hand, we found little evidence for a value-enhancing use of publications for appropriation purposes. Overall, our study provides support for the increasingly strong view among scholars that minimizing knowledge outflows may not be an optimal choice for firms and that they should instead strategically disclose knowledge.

Some heterogeneity concerning the impact of scientific activities was found. A negative but nonsignificant sign was found for ICT sectors. Instead, a strong positive relationship was observed in the instruments sectors. Therefore, appropriability conditions would seem to matter, which implies that R&D managers need to carefully consider the benefits and potential costs caused by related spillovers. To obtain a better understanding of the mechanisms involved, future work could focus on contextual conditions that potentially moderate the relationship between scientific activities and the firm's market value. In conclusion, the strengths and weaknesses of the market value approach and corresponding empirical limitations should be kept in mind when interpreting results. Financial markets can be very volatile and do not behave completely rationally. Thus, future research could complement our present study by using direct financial performance measures. This however, would entail dealing explicitly with the time lags between knowledge creation and commercial returns.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2015.2220.

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